The Dissertation Committee for Conan Christopher Crum Certifies that this is the approved version of the following dissertation:

Oil, Pollution, and Crime: Three Essays in Public Economics

Committee:

Don Fullerton, Supervisor

Roberton C. Williams, III, Supervisor

Russell W. Cooper

P. Dean Corbae

Charles G. Groat

Oil, Pollution, and Crime: Three Essays in Public Economics

by

Conan Christopher Crum, B.A.; M.S.

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May, 2008

Dedication

This dissertation is dedicated to my wife Amy Bryce Crum.

Acknowledgements

I wish to thank my supervisors Don Fullerton and Rob Williams and my other committee members, Russell Cooper, Dean Corbae, and Charles Groat. I would also like to thank my fellow graduate students especially, Jason DeBacker, Pablo D'Erasmo, Tim Jones, Barry Kahn and Anya Yurko. Chapter 3 of this dissertation is co-written with Barry Kahn.

Oil, Pollution, and Crime: Three Essays in Public Economics

Publication No._____________

Conan Christopher Crum, Ph.D.
The University of Texas at Austin, 2008

Supervisors: Don Fullerton and Roberton C. Williams, III

The overall goal of this dissertation is to study important questions in public economics. In its three chapters, I look at peak world oil production and its implications for oil prices; cross-country pollution emission rates and implications for institutional quality; and finally, black-white arrest rates and implications for law enforcement discount factors. Each chapter of this dissertation combines new theory with robust empirical work to extend the quantitative frontier of research in public economics.

Table of Contents

List of Tables ix

List of Figures x

Chapter 1: The Economics of Peak Oil 1

1.1 Model 6

1.1.1 The Production Manager's Problem 6

1.1.2 The Development Manager's Problem 9

1.1.3 The Exploration Manager's Problem 10

1.1.4 Competitive Equilibrium 11

1.1.5 Solving the Model 12

1.2 Estimation of Non-OPEC Oil Production 14

1.2.1 Overview of Simulation Procedure 15

1.2.2 Non-OPEC Data and Moments 15

1.2.3 Estimation Results 17

1.2.4 Simulating the Estimated Model In-Sample 1980-2006 20

1.3 Forecasting Future World Oil Production and Prices 23

1.3.2 World Oil Demand and World Economic Growth 25

1.3.3 Equilibrium World Oil Production and Price Forecast 27

1.3.4 Baseline Forecast: Constant OPEC Market Share 29

1.3.5 World Oil Production and Price Forecast: Declining OPEC Market Share 34

1.3.6 World Oil Production and Price Forecast: Increasing OPEC Market Share 37

1.4 Conclusion and Suggestions for Further Research 40

Chapter 2: Do Ethnic Differences Inhibit the Provision of Environmental Public Goods? 43

2.1 Theoretical Model 47

2.2 Statistical Model 50

2.2.1 Equation Structure 51

2.2.2 The Data 54
2.3 The Results 57
2.3.1 Unconditional Correlations 57
2.3.2 Regression Results 59
2.4 Robustness Check 62
2.4.1 Data 63
2.4.2 Results 64
2.5 Conclusion 66

Chapter 3: Divergence Followed By Convergence: The Propagation of Arrest Rates in Victimless Crimes 68
3.1 Data 71
3.2 The Model 76
3.3 Static Problem 82
3.4 Conclusion 87

Appendix 89

References 91

Vita 96

List of Tables

Table 1.1: Log Real Oil Prices 13

Table 1.2: Moments 18

Table 1.3: Model Parameters 19

Table 1.4: World Oil Demand 25

Table 1.5: World Economic Growth....................26

Table 2.1: Cross-Country Summary Statistics....................55

Table 2.2: Determinants of Cross-Country Emissions 60

Table 2.3: Determinants of Local-Level Ambient Water Quality 65

List of Figures

Figure 1.1: In-Sample Non-OPEC Oil Production 21

Figure 1.2: In-Sample Non-OPEC Oil Reserves 22

Figure 1.3: OPEC's Share of World Oil Production...24

Figure 1.4: World Oil Production Constant OPEC Market Share 31

Figure 1.5: Real Oil Prices Constant OPEC Market Share....................................33

Figure 1.6: World Oil Production Decreasing OPEC Market Share 35

Figure 1.7: Real Oil Prices Decreasing OPEC Market Share 36

Figure 1.8: World Oil Production Increasing OPEC Market Share.......................38

Figure 1.9: Real Oil Prices Increasing OPEC Market Share 39

Figure 2.1: Emissions and Ethnic Fractionalization 58

Figure 3.1: B-W Ratio for Drug Arrests 68

Figure 3.2: B-W Ratio for Prostitution Arrests...69

Figure 3.3: Per Capita Drug Arrests 1933-1969 74

Figure 3.4: Per Capita Drug Arrests 1970-2004 75

Figure 3.5: Per Capita Prostitution Arrests 1934-2004...76

Figure 3.6: DFC Paths for Varying β's..81

Figure 3.7: Prostitution Arrests 1934-2004 84

Figure 3.8: Drug Arrests 1945-1965...85

Figure 3.9: Drug Arrests 1970-2004...86

Chapter 1: The Economics of Peak Oil

Oil is likely the most important commodity to the world economy. Hence, the future paths of world oil production and world oil prices have strong implications for policy makers and private individuals alike. Several models have forecasted future oil output levels by combining an estimate of total recoverable reserves with a deterministic trend in production. Unfortunately, models that focus on total recoverable reserves and exogenous production trends are unable to say anything about the price that might accompany a given future oil production path, and they ignore the profit maximization problem facing oil producers. A structural model of oil production is needed to shed light on both the future of world oil production and world oil prices, and the model needs to be quantitative in nature. Without quantitative implications, a structural model of world oil production provides little more benefit to real world decision makers than a mechanistic model that uses a total recoverable reserve level and assumes an exogenous production path. The goal of this chapter is to bring together new theory and data from the world oil markets to make a quantitative forecast of future world oil production and prices.

While mechanistic models of oil production abstract completely from world oil demand and producer profit maximization, such models have been remarkable effective at matching the oil output of particular oil producing regions, most notably the oil production of the United States as a whole. Hubbert (1956) predicted that US oil production would peak between 1965 and 1970. Indeed, US oil production did peak in 1970. Hubbert made his prediction under the assumption that cumulative oil production follows a logistic growth path, and his methodology has inspired numerous predictions of a coming world oil shortage.[1] Recently, the Energy Information Agency (EIA 2004) predicted in their baseline scenario that world oil production would peak in 2037 at a production level of 53.2 billion barrels (bbl). This prediction is obtained by first estimating world total recoverable reserves and then assuming a 2% oil production growth rate up to peak production, followed by declining production thereafter, such that a constant reserve to production (RP) ratio of 10 is maintained in post-peak production years. Similar to the Hubbert methodology, these assumptions are based on physical and historical relationships rather than economics. The EIA (2004) makes no predictions about future world oil prices.

In the economics literature, Hotelling (1931) represents the seminal work in the theory of non-renewable resource extraction. In his model, production is allocated across time in order to equilibrate the returns on resources and the returns of other assets in the economy. The result of this logic is the "Hotelling Rule," which states that the price of oil is expected to rise at the rate of interest.[2] Pindyck (1978) expands the theory of Hotelling (1931) to include exploration and finds that non-renewable production paths can be either always rising, always falling, or hump shaped, depending upon the structure of production and exploration costs and demand. In contrast to the predictions of mechanistic models, the Hotelling (1931) framework never predicts unforeseen oil shortages, because rational expectations mean that future shortages would be anticipated and result in sharply increasing oil prices. Hence, rational investors would save oil to sell at those high prices—undoing those future shortages. Other notable extension of the

[1] See Campbell (1997), Campbell and Laherrere (1998), Deffeyes (2002, 2005), and Reynolds (2002).

theory of non-renewable resource extraction include Mason (2001), Thompson (2001), Cairn and Van Quyen (1998), Van Quyen (1991), and Litzenberger and Rabinowitz (1995).

Many of the theory papers cited above have an empirical component to them. This empirical component usually takes the form of hypothesis testing on reduced form equations that are implied by the theoretical model. None of these models are structurally estimated using data on production, reserves and prices from a particular region or the world. Survey papers such as Gately (1984) and Cremer and Salehi-Isfahani (1991) and the Energy Modeling Forum of Stanford University (1984, 1995) summarize the more data-oriented side of the non-renewable resource economics literature. The goals of these papers are to match the actual oil production levels we see from OPEC and non-OPEC countries, as well as world oil production and prices. In order to do this, these models incorporate multiple types of supply and demand elasticities, and they focus on production rules of thumb that are consistent with producers who display bounded rationality. For instance, Gately (2001) correctly predicts that the EIA forecast for OPEC oil production is much too high, and Gately and Huntington (2001) show that the price elasticity of oil demand is different for price increases compared to price decreases.

While these models have rich empirical implications and predictive power they are, however, subject to the Lucas critique because they abstract from the explicit profit maximization problem that oil producers are solving. Hence, the supply elasticities

[2] This rule can be elaborated in many ways. With extraction costs, for example, it is the scarcity rent portion of the price that rises at the rate of interest.

estimated in these models are only based on historical relationships observed in the data. However, it is important to remember that these historical relationships could break down, since the true elasticities of supply are functions of the deep parameters that govern the costs of oil exploration, development, and production.

The purpose of this chapter is to use a structural model to forecast world oil production and prices out into the future. In order to do this, a structural model of non-OPEC oil production is proposed in which exploration, development and extraction are each explicitly modeled. The overall model is then estimated by simulated method of moments (SMM), using non-OPEC production, reserve, and discovery data from 1980-2006. The estimated model is then combined with OPEC-targeted market shares and an estimated world demand for oil, in order to produce forecasts of future equilibrium oil output and price levels. The assumption that OPEC targets a specific market share is similar to that of Gately (2004). In Gately (2004), however, the reference case for non-OPEC oil production is taken as exogenous according to EIA estimates. Neither Gately (2004) nor the EIA (2004) model the profit maximization problem facing non-OPEC oil producers.

This chapter makes two main contributions to the literature. First, this chapter provides the first structural estimation of worldwide non-OPEC oil production. Second, it uses this structural model of oil production and an estimated demand for world oil to forecast equilibrium oil output and price levels into the future. In the model presented in this chapter, the demand for oil interacts with resource scarcity to generate endogenously equilibrium oil prices and exploration, development and extraction activity. Thus, this chapter combines the structural modeling of the theoretical resource literature with the forecasting and data emphasis from the empirical literature on world oil supply and demand.

The finding here is that world conventional oil production is likely to peak around the year 2045 at an annual production level of 52 billion bbl. The baseline forecast in this chapter is similar to a 2004 EIA forecast that predicts a peak in world oil production in the year 2037 at an annual production level of 53.2 billion bbl. The EIA predicts a sharp decline in production after 2037, while this chapter finds that production will likely remain relatively flat both before and after the peak production year. The baseline forecast here is that world oil production will remain above 50 billion bbl for nearly two decades. The results in this chapter are also strictly at odds with impending world oil shortage scenarios forecasted by those using the methodology of Hubbert (1956).

This chapter also finds that equilibrium world oil prices are likely to fall substantially from their recent highs. This chapter forecasts that real oil prices will return to levels similar to those observed in the 1990s. However, real oil prices will begin a gradual rise starting in about 2025. The upward trend in real oil prices continues for most of the century before leveling off at price of over $80/bbl in 2000 constant dollars.

This chapter is organized as follows. Section 1.1 presents the model, while Section 1.2 presents the result of the in-sample estimation using data from 1980-2006. Section 1.3 presents the forecasts for equilibrium world oil production and prices for the period 2007-2107. Section 1.4 concludes the chapter and discusses additional research to be done.

1.1 MODEL

In modeling the representative non-OPEC oil producer, I assume that three separate decision makers interact in the production process. In chronological order, the exploration manager first searches for new oil discoveries, the development manager decides when to drill new oil wells, and finally, the production manager extracts the oil. In considering whether or not to explore another oil field, however, the exploration manager takes into account the value that will subsequently be created by the actions of the development and production managers. Likewise, in deciding whether or not to drill another well, the development manager takes into account the value that the production manager will create through his choices about extraction. Since the decisions of the managers who act first, depend upon the value created by the managers who act later, the presentation of the model proceeds in reverse chronological order.

1.1.1 The Production Manager's Problem

Given a drilled well, the production manager seeks to maximize the expected discounted value of that well. The optimal oil extraction problem facing this production manager is:

(1.1) $$V^D(P,r) = \max_{r'} \Pi(P,r,r') + \beta E_{P'|P}[V^D(P',r')]$$

(1.2) $$\Pi(P,r,r') = Px - c(x,r)$$

(1.3) $$x = r - r'$$

In equations (1.1-1.3), V^D is the maximum value of a drilled well, P is the current real oil price, r is recoverable reserves, x is the amount of oil extracted, β is the discount factor common to all managers and c is the total cost of extraction. A prime denotes next period's variables. Lower case letters denote an individual manager's variables, whereas upper case letters denote aggregate variables.[3]

The extraction cost function used in this chapter is:

(1.4) $c(x,r) = c_0 x + c_1(\psi r - x)^2$.

In this equation, c_0 is the constant cost per unit of extraction that is independent of the level of reserves, while ψ is the fraction of reserves such that the product ψr equals the cost-minimizing extraction level. Positive values of c_1 impose a penalty when extraction, x, deviates from the cost-minimizing extraction level ψr.

Havlena and Odeh (1963, 1964) show that the material balance equation as applied to oil reservoirs can be written as:

(1.5) $x = r(E_o + mE_g + E_{f,w}) + W_e B_w$,

where E_o represents the expansion of oil and dissolved gas, m is the ratio of the pore volume of the gascap to the pore volume of oil, E_g represents the expansion of the gascap, $E_{f,w}$ represents expansion of water and the reduction of hydrocarbon pore volume, W_e is the cumulative water influx into the oil reservoir, and B_w is the water volume in the oil formation.[4]

---

[3] One exception to this notation rule is the real price of oil. Upper case P denotes the real price of oil which is an aggregate variable, but lower case p is the log of the real price of oil (which is also an aggregate variable).

[4] When a production well is drilled into an oil reservoir, a pressure difference arises between the surface and the reservoir. If this pressure difference is great enough, oil will flow naturally from the reservoir to

Havlena and Odeh show that in many cases equation (1.5) can be interpreted as a linear function. In a pure gas drive well, for instance, the absence of water means $E_{f,w} = 0$ and $B_w = 0$,then equation (1.5) reduces to:

(1.6) $x = r(E_o + mE_g)$.

Thus, in this case, the extraction level is determined by the natural expansion of oil and dissolved gas, and the expansion of the gascap scaled by the gascap to oil pore volume ratio.

Another example of a case where equation (1.5) reduces to a linear function of reserves is in a well with limited water influx. In these wells $W_e = 0$, and equation (1.5) reduces to:

(1.7) $x = r(E_o + mE_g + E_{f,w})$.

Hence, in all cases where water is either absent or the water influx is minimal, the natural flow of oil to the surface is just a linear function of the remaining reserves. Thus, the parameter ψ is the percentage of reserves that naturally flow to the surface based upon the average geology of non-OPEC oil formations. Production can deviate from ψr, but only at a cost of $c_1(\psi r - x)^2$.

---

the surface. The natural rate of flow is determined by the physical properties of the fluids in the reservoir and the pressure differential created by the production well. Commonly, the top of a reservoir contains a gascap of natural gas, the middle contains oil, and the bottom contains water. Of course reservoirs also contain rocks and other solids. The pore volume represents the fluid volume of a reservoir. As oil in the reservoir is pumped out, the gascap and water table expand, maintaining much of the pressure differential around the production well.

1.1.2 The Development Manager's Problem

Given the past discoveries of oil by the exploration manager and the future value to be created by the production manager, the problem facing the development manger is a discrete choice decision of whether or not to drill a new well. Hence, the optimization problem facing the development manager is:

(1.8) $$V^{UD}(P,r,w) = \max\{\beta E_{P'|P}[V^{D}(P',r)] - w, \beta E_{P',w'|P}[V^{UD}(P',r,w')]\}.$$

In this equation, V^{UD} is the maximum value of an un-drilled well, and w is the cost of drilling a new well. The fixed cost of drilling, w, differs across development managers; the development manager each period draws a new w from an independent and identical distribution. The possible drilling costs, w, are described by a uniform distribution:

(1.9) $$w \sim U(0,W).$$

The uniform distribution for drilling cost is similar to the uniform production cost assumption of Litzenberger and Rabinowitz (1995).

The purpose of heterogeneity in the drilling costs is to allocate the development of total reserves amongst various development managers in a tractable and realistic manner. If the expected discounted value of an un-drilled well next period is greater than the expected value of deciding to drill today, then the development manager decides not to drill another production well. Also, in equation (1.8) the value of a drilled well, V^D, is discounted by one period in order to account for real world construction lag times between the decision to drill and the completion of a new oil well.

1.1.3 The Exploration Manager's Problem

The problem facing the exploration manager is either to explore a new field in the current period or leave it unexplored for the next period. The value of an unexplored a field is determined by two factors. One factor is the recoverable reserves expected to be discovered if the field is explored. These reserves determine the optimal number of new wells that can be drilled. The second factor is the cost of exploring the field. Thus the optimization problem of the exploration manager is:

$$\begin{aligned}(1.10)\quad & V^{UF}(P,r,N,CD)= \\ & \max\{\beta E_{P',w',n|P}[n\cdot V^{UD}(P',r,w')]-f(N,CD),\beta E_{P',N',CD'|P}[V^{UF}(P',r,N',CD')]\}\end{aligned}$$

In this equation, V^{UF} is the maximum value of an unexplored field, f is the fixed cost of exploring a field, N is the number of oil firms that enter to explore in a given period, and CD is the cumulative discoveries of oil to date. Also, n is a random variable realized after the field has been explored that represents the number of new wells that can be drilled on a field. The random variable n is assumed to be distributed log-normal:

$$(1.11)\quad n \sim LogN(1,\sigma_n).$$

The variable n is assumed to be log-normal so that discoveries are non-negative and distributed with curvature. If the exploration manager chooses to explore the field, then the payoff is the expected discounted value of the number of wells likely to be discovered times the value of an un-drilled well ($\beta E_{P',w',n|P}[n\cdot V^{UD}(P',r,w')]$) less the fixed cost of exploration ($f(N,CD)$). If the exploration manager chooses not to explore the field, then the payoff is the expected discounted value of an unexplored field in the next period ($\beta E_{P',N',CD'|P}[V^{UF}(P',r,N',CD')]$).

Note that the left-hand side of equation (1.10) implies that the maximum value of an unexplored field, V^{UF}, depends on four factors: the price, P, the recoverable reserve level, r, the number of firms that enter to explore, N, and the cumulative discoveries to date, CD. The price and recoverable reserve level are both stationary variables. However, the number of firms that enter and the cumulative discoveries are not. Thus, in order to solve the model, it is essential that the fixed cost of oil exploration can be solved as a function of the stationary variables alone.

1.1.4 Competitive Equilibrium

I assume that non-OPEC oil companies are competitive, and that entry is free at the exploration stage. With free entry, the value of an unexplored field must equal zero, and then the expected discounted value of an un-drilled well must equal the fixed cost of exploration. Hence, in a competitive equilibrium with free entry, the following equation must hold in all periods and all states.

$$(1.12) \quad \beta E_{P',w',n|P}[n \cdot V^{UD}(P',r,w')] = f(N,CD)$$

Thus, the fixed cost of exploration is only a function the stationary variables P, r, and w. In equilibrium, the fixed cost of oil exploration is also a stationary variable.

The following functional form assumption is made about the fixed cost of exploration:

$$(1.13) \quad f(N,CD) = \exp[N/(\gamma_0 CD + \gamma_1 CD^2)].$$

This functional form is chosen for two reasons. First, the fixed cost of exploration is increasing and convex in N. This assumption is made since it is likely that, all else equal, more entrants raise the exploration costs for all firms. This reflects the fact that the inputs to exploration, such as drill bits and petroleum engineers, are likely to be capacity constrained in a given period. Second, it allows for the cost of exploration to be either increasing or decreasing in cumulative discoveries, depending on the level of CD and the values of γ_0 and γ_1.

Using the cumulative discoveries to date, the number of firms that enter in equilibrium, N^e, can be derived by combining equations (1.13) and (1.12).

(1.14) $N^e = (\gamma_0 CD + \gamma_1 CD^2)\log(\beta E_{P',w',n|P}[n \cdot V^{UD}(P',r,w')])$

Equation (1.14) details the equilibrium number of firms that must enter to explore fields in order to ensure that the zero expected profit condition holds every period. New discoveries for a period are determined by the number of entrants (N^e) and the realization of the stochastic discoveries variable (n). This model has no upperbound on cumulative discoveries. Discoveries in every period are determined endogenously by the number of entrants necessary to keep the cost of exploration, $f(N, CD)$, equal to the benefits of exploration, $\beta E_{P',w',n|P}[n \cdot V^{UD}(P',r,w')]$.

1.1.5 Solving the Model

In order to solve the model for the decision rules of the three managers (production, development and exploration), it is necessary to determine the expectations for future prices. I assume that non-OPEC oil producers expect log real oil prices to follow a stationary auto-regressive process with one lag, AR(1).

(1.15) $p_t = \rho_p(p_{t-1} - \mu_p) + \mu_p + \varepsilon_{p,t}$

(1.16) $\varepsilon_p \sim N(0, \sigma_p^2)$

In equation (1.15), the variable p represents the log real oil price, ρ_p is the auto-correlation in log real oil prices, μ_p is the mean log real oil price, and ε_p is a normally distributed, independent shock to real oil prices.

Table 1.1: Log Real Oil Prices

Parameter	Coef	Std Err
μ_p	2.8921	0.1709
ρ_p	0.9051	0.0359
σ_p	0.2193	0.0114

Equation (1.15) is estimated using average annual real oil prices from 1870 – 2006. Average annual nominal oil prices are obtained from the EIA, and those nominal prices are deflated by the US GDP deflator with a base year of 2000. The results from the estimation are displayed in Table 1.1.

The coefficient estimates in Table 1.1 are all statistically different from zero and measured with a high degree of precision. The estimate of μ_p is 2.8921 which corresponds to a real oil price of 18.03 in constant 2000 US dollars. The estimate of ρ_p equal to 0.9051 indicates that real oil prices have a high degree of persistence, but it does not imply a unit root or non-stationary process for real oil prices. In fact, using an augmented Dickey-Fuller test, one can reject the presence of a unit root at the 1% level.

The results from Table 1.1 are then used to create a ten-state Markov process using the method described in Tauchen and Hussey (1991). This discrete Markov process describes the representative non-OPEC oil producer's expectations about future real oil prices.

With expectations of future prices determined, the decision rules for the three managers' problems are solved numerically using value function iteration. These decision rules are then combined with a set of initial conditions to simulate the model over time. To estimate the model parameters, the simulations from the model are then compared to the data on non-OPEC oil production, reserves and discoveries.

1.2 ESTIMATION OF NON-OPEC OIL PRODUCTION

Except for the discount factor, β, and the constant cost of extraction, c_0, all the model parameters described in Section 1.1 are estimated using SMM according to the strategy outlined in Lee and Ingram (1991). The discount factor is set to 0.9, consistent with the findings of Adelman (1993), and the constant cost of extraction is set equal to 0.75, which is consistent with the findings of the EIA (2006). I define the vector θ to contain the six model parameters to be estimated:

(1.17) $\theta = \{c_1, \psi, W, \sigma_n, \gamma_0, \gamma_1\}$.

The model can be fully solved and simulated over time for any given values of the parameter vector θ, a realization of prices, a level of cumulative discoveries, a number of drilled wells and a number of undrilled wells.

1.2.1 Overview of Simulation Procedure

The number of firms that enter to explore oil fields in each period can be determined according to equation (1.14). The number of entrants in a given period and the realization of the random variable n determine the new oil discoveries for each period. The new oil discoveries plus the number of undrilled wells remaining from the previous period determines the total possible number of new wells that can be drilled. Given the total number of new wells that could be drilled, the decision rules from the development manager's problem, and the realization of the stochastic drilling cost, w, determines the actual number of new wells drilled in each period. Using their own decision rules, production managers optimally choose the extraction levels both for newly drilled wells and for wells drilled in previous periods. These extraction levels can be combined to create an aggregate oil production time series, X. In addition, a time series of aggregate discoveries, D, can be recovered from the number of exploration entrants and the realizations of n. Finally, a time series of aggregate reserves, R, can be calculated by summing the number of reserves remaining within drilled and undrilled wells. These three time series plus the simulated price time series are used to calculate moments from the model. The model moments are then compared to actual non-OPEC data moments in order to update the parameter vector θ.

1.2.2 Non-OPEC Data and Moments

While non-OPEC oil production data are available back to 1965, non-OPEC reserve data are only available starting in 1980. Hence, the moments used to estimate the model come from the period 1980-2006 and are the following: the average growth rate of production $\mu(g_X)$, the standard deviation of the growth rate of production $\sigma(g_X)$, the average growth rate of reserves $\mu(g_R)$, the standard deviation of the growth rate of reserves $\sigma(g_R)$, the correlation between production and prices $\rho(X,P)$, the correlation between production and discoveries $\rho(X,D)$, and the coefficients, b_0 and b_1, from regressing discoveries on cumulative discoveries and cumulative discoveries squared.[5] All data on non-OPEC reserves and production come from the BP Statistical Review (2007). Non-OPEC discoveries are calculated using the following identity:

(1.18) $D = R' - R + X$.

Hence, aggregate non-OPEC discoveries represent both the reserve growth at entirely new fields and the reserve growth due to improved recovery technologies. This enables the estimation of the model to capture both important sources of reserve growth.

The vector of differenced moments used in the minimization routine is:

(1.19) $g(\theta) = H(Z) - H_S(Y(\theta))$,

where the matrix Z contains the aggregate variables, X, R, D, and P, from the data on non-OPEC oil production, reserves, discoveries and real oil prices in constant 2000 US dollars. The function H transforms the aggregate variables from the data in matrix Z into the sample data moments. The matrix Y contains the aggregate variables, X, R, D, and P, from the simulations of the model. Those aggregate variables are a function of

[5] Specifically, the coefficients b_0 and b_1 come from running a regression, $D = b_0 CD + b_1 CD^2$, where D is discoveries and CD is cumulative discoveries.

the model parameters θ. The function H_S transforms the matrix Y into the simulated moments from the model.

The following optimization routine is used to estimate the model parameters.

(1.20) $\min_{\theta} g(\theta)'\Omega^{-1}g(\theta)$

The matrix Ω is the optimal weighting matrix for the criterion function, $g(\theta)'\Omega^{-1}g(\theta)$. In this chapter, an estimate of Ω is obtained by using a jackknife procedure to estimate variance-covariance matrix of the data moments as described in Greene (2003). The model parameters that minimize equation (1.18) are found using the simplex algorithm of Nelder and Mead (1965).

1.2.3 Estimation Results

Table 1.2 displays the targeted moments from the data and the same moments calculated from simulating the model using the parameter vector that minimized equation (1.20). The optimized model is able to match most of the moments very well. The model displays a lower standard deviation in the growth rate of reserves (1.28%) than does the data (2.64%). Also, the correlations $\rho(X,P)$ and $\rho(X,D)$ are higher in the model than in the data. The differences between the model moments and the non-OPEC data moments are likely the result of two factors.

Table 1.2: Moments

Moment	Non-OPEC Data	Model Simulation
$\mu(g_X)$	1.10%	0.98%
$\sigma(g_X)$	1.55%	2.14%
$\mu(g_R)$	1.01%	1.03%
$\sigma(g_R)$	2.64%	1.28%
$\rho(X,P)$	-0.0478	0.1863
$\rho(X,D)$	0.2013	0.4499
b_0	0.0326	0.0356
b_1	-9.50E-06	-1.43E-05

First, the model only contains two aggregate shocks: the random component of prices and the random component of discoveries. In the data, however, other factors outside of fluctuations in prices and discoveries are likely to influence the time series of non-OPEC oil production, reserves and discoveries. Hence, it is natural to expect the correlations $\rho(X,P)$ and $\rho(X,D)$ to be higher in the model than in the data. The model is able to match the stronger correlation between oil production and discoveries, relative to the correlation between production and prices that we see in the data. In addition, the correlation between oil production and prices is the moment measured with the highest degree of statistical uncertainty. The correlation between oil production and prices has a coefficient of variation over eighty times larger than any other moment. Hence, that moment receives the least weight in the minimization of the criterion function.

The second reason that the moments from the model differ from those in the data is the degree to which non-OPEC oil production deviates from perfect competition. Under perfect competition, the standard deviation in the growth rate of production will almost always be above the standard deviation in the growth rate of reserves. This is because fluctuating oil production with prices increases profits, while changing oil reserve levels does not. However, if production decisions are influenced by slow moving regulatory controls, it could reverse the relative sizes of the standard deviation of the growth rate of production and the standard deviation of the growth rate of reserves.

Table 1.3 reports the point estimate and standard errors for the model parameters. In the model, a unit of extraction is taken to be 1,000 barrels (bbls). Hence, the point estimate for c_1 corresponds to a $111.17 penalty in constant 2000 US dollars for a 1,000 bbl deviation from the cost-minimizing extraction rate of ψr. The point estimate for W indicates a uniform distribution for w between zero and 936. In other words, the maximum drilling cost for a single well is approximately $936 per 1,000 bbl of reserves. Thus, in the model, the cost of drilling a well over an oil reservoir of million bbl would range from zero to almost a million dollars.

Table 1.3: Model Parameters

Parameter	Point Est	Std Err
c_1	111.17	40.855
ψ	0.071125	0.00354
W	936.15	314.85
σ_n	0.14628	0.0229
γ_0	6.30E-05	5.62E-06
γ_1	-2.04E-08	5.94E-09

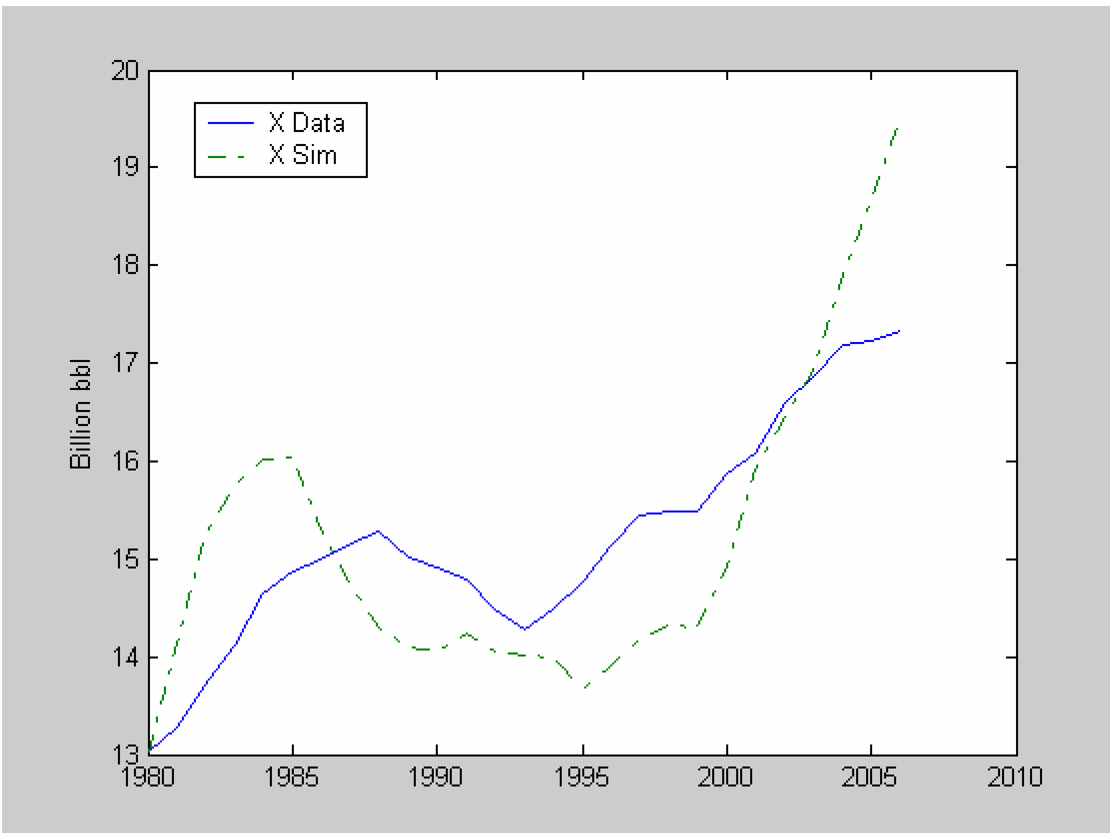
The point estimate for ψ of 0.0711 implies that the average cost-minimizing extraction rate for non-OPEC wells is 7.11% of remaining reserves. The point estimate for σ_n of 0.14628 implies that oil exploration yields actual discoveries that have approximately a 14.6% standard deviation around the mean discovery level. Finally, the positive point estimate of γ_0 and the negative point estimate of γ_1, combined with the current cumulative discoveries to date, indicate that non-OPEC oil exploration will continue to experience entry, at least in the short term. All of the parameter estimates are well identified by the moments and are statistically different from zero at any standard level of significance.

1.2.4 Simulating the Estimated Model In-Sample 1980-2006

Figure 1.1 displays the result from the in-sample simulation for non-OPEC oil production. The line denoted as 'X data,' shows the actual level of non-OPEC aggregate oil production from 1980-2006. The line denoted as 'X sim,' shows the level of aggregate oil production generated by the simulated model, when the actual real oil prices and non-OPEC discoveries over the period 1980-2006 are fed into the model as inputs. The model parameters are set equal to their point estimates in Table 1.3. In order to initialize the simulation, the model is calibrated to match the oil production in all previous periods exactly.

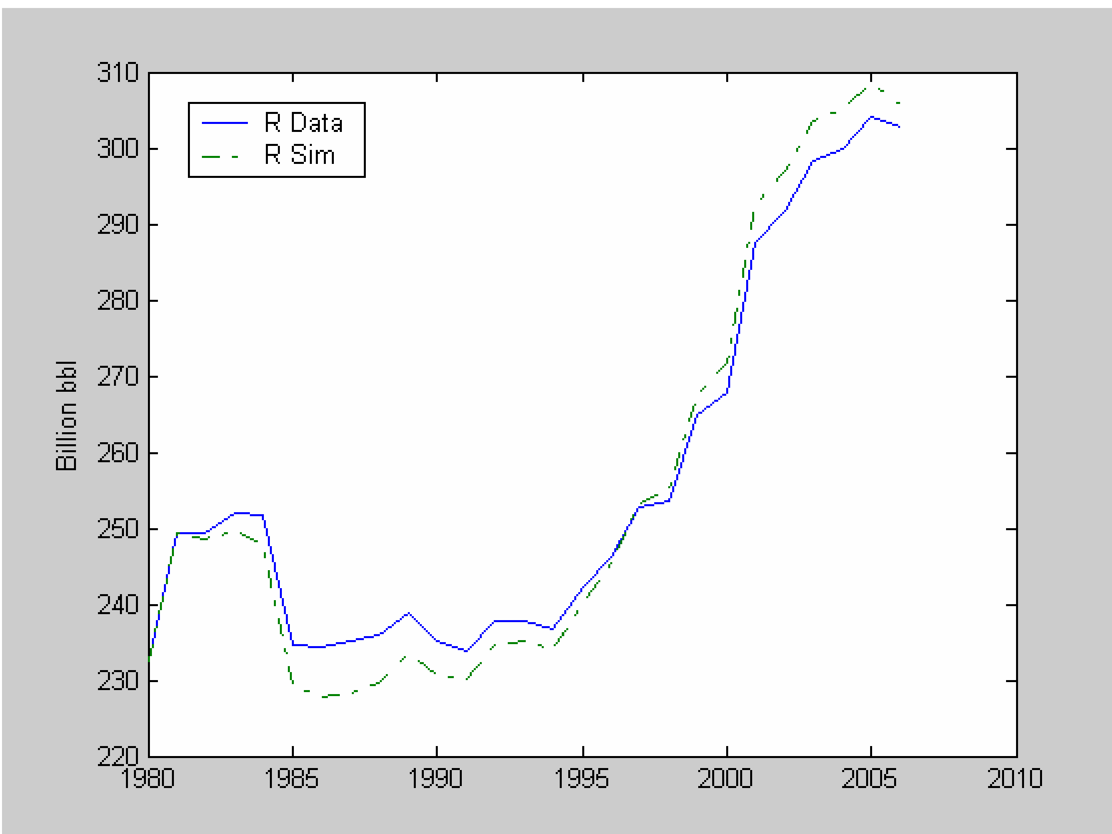
As can be seen in Figure 1.1, the model captures the general movement in non-OPEC production quite well. The correlation between the growth rate in aggregate oil production in the model and in the data is strong at 0.441. The model displays higher oil production levels than the data in high price periods like the early 1980s and 2004-2006, and lower oil production level in low price periods like the latter half of the 1990s. This difference might be expected, however, given the higher correlation of production and prices present in the model relative to the data, as discussed earlier. It should be noted that non-linear least squares is not used in the estimation process. Hence, none of the model parameters are chosen to match the oil production curve in Figure 1.1. The model parameters are chosen to match the non-OPEC data moments displayed in Table 1.2.

Figure 1.1: In-Sample Non-OPEC Oil Production



Next, Figure 1.2 displays the result from the in-sample simulation for non-OPEC oil reserves. The line denoted as 'R data,' shows the actual level of non-OPEC oil reserves from 1980-2006. The line denoted as 'R sim,' shows the level of oil reserves generated by the model. Whereas Figure 1.1 displays the flow of oil from the model and the data, Figure 1.2 displays the stock. Hence, the difference between the reserve levels in the model and the data represent the cumulative oil production differential between the model and the data. As expected from the Figure 1.1, the relatively higher oil production in the model in the early 1980s creates lower reserve levels in the model when compared to the data. The reserve levels in the model then rise above those in the data as the production in the model falls relative to the oil production in the data.

Figure 1.2: In-Sample Non-OPEC Oil Reserves



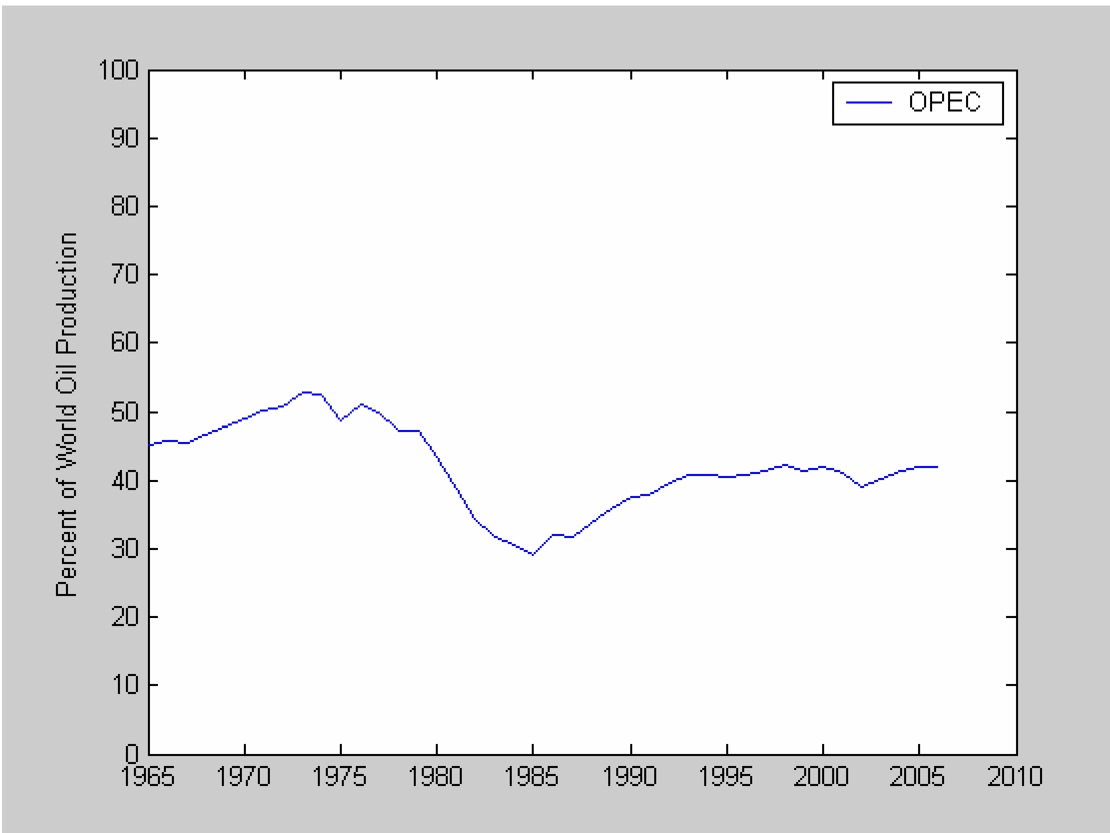
1.3 FORECASTING FUTURE WORLD OIL PRODUCTION AND PRICES

In order to forecast future oil production and prices, dynamic oil supply and demand functions must be derived. The results from Section 1.2 demonstrate that the model defined in Section 1.1 does a good job of replicating some of the key features of the non-OPEC oil data. However, a model of world oil production requires a modeling choice about future OPEC oil production. This model of world oil supply must then be brought together with a world demand for oil in order to forecast equilibrium oil prices and production levels.

1.3.1 OPEC Oil Production

Following the methodology of Gately (2004), this chapter assumes that OPEC seeks to target a specific share of the world oil market. This assumption is made for four reasons. First, as shown in Figure 1.3, OPEC's share of the world oil market has been fairly constant over time. OPEC's market share from 1965-2006 has averaged around 42% of world oil production, and this market share has been extremely stable since 1992. Second, OPEC's commitment to collude and exercise market power varies over time. Hence, it is extremely difficult to model the complex game that OPEC members play, not only with the rest of the world, but also amongst themselves. Third, it is not at all clear that OPEC is a profit maximizer. Oil revenues make up a substantial portion of government receipts for OPEC member countries. Thus, to the extent that insurance is less than complete, they may value oil revenue certainty in addition to profits. Fourth, at least in the case of the 1973 Arab Oil Embargo, OPEC seems to have made production decisions largely for political reasons. Hence, it is difficult to know how even to model the payoffs to OPEC member countries, when different oil production levels help to satisfy different competing goals.

Figure 1.3: OPEC's Share of World Oil Production



Nonetheless, endogenizing OPEC's production response certainly represents a worthy extension to the work presented here. For clarity and tractability, however, this chapter focuses on exogenous OPEC market shares. For my analysis, three exogenous OPEC market share processes are considered. In the baseline model, OPEC market shares are assumed to remain constant at their historic average of 42% of world oil production. For two possibilities that bound the assumption of stability, I consider the case where OPEC's fraction of the world oil market drops by 0.5% each year, and another where OPEC's market share increases by 0.5% each year.

1.3.2 World Oil Demand and World Economic Growth

The supply side of the world oil market is defined by combining the structural model of non-OPEC oil production estimated in Section 1.2 with each of the three market share assumptions about OPEC oil production. However, in order to forecast equilibrium world oil prices and production into the future, the demand side of the model must be estimated as well. The structure of the estimated world oil demand is:

(1.21) $\log(Q_{D,t}) = \alpha_0 + \alpha_1 \log(Q_{D,t-1}) + \alpha_2 \log(P_t) + \alpha_3 G_t + \varepsilon_{D,t}$.

In this equation, $Q_{D,t}$ represents the quantity of oil demanded in period t, P is the real price of oil, G is world economic growth calculated as first differenced log world gross domestic product, and ε_D is the error term in the world oil demand equation.

Table 1.4: World Oil Demand

Variable	Coefficient	Std Err
$\log(Q_{D,t-1})$	0.9837	0.0050
$\log(P_t)$	-0.0358	0.0078
G_t	1.7033	0.2270
Constant	0.1191	0.0284

Table 1.4 displays the result from estimation of equation (1.21). The coefficients in Table 1.4 are estimated using ordinary least squares, and the standard errors are adjusted for possible heteroskedasticity and autocorrelation in the error term using the method of Newey and West (1987). The coefficient on lagged demand of 0.9837 implies that world oil demand is extremely persistent from one period to the next. However, the hypothesis that the coefficient on lagged demand is equal to one is rejected at the 5% level. The coefficient on log real oil prices implies that a 1% increase in real oil prices reduces world oil demand by 0.0358% in that same period. Hence, only large price changes have meaningful effects on world oil demand. The coefficient on economic growth of 1.7033 implies that a 100 basis point increase in world economic growth would increase world oil demand by just over 1 billion bbl.

World economic growth is assumed to follow an AR(1) process described by:

(1.22) $G_t = \mu_G + \rho_G (G_{t-1} - \mu_G) + \varepsilon_{G,t}$.

In this equation, μ_G is the mean growth rate in world output, ρ_G is the auto correlation in world output growth, and ε_G represents independent shocks to world economic growth that are distributed $N(0, \sigma_G^2)$. The AR(1) process in equation (1.22) is estimated over the period 1965 – 2003 using the data on real world output from Maddison (2003).

Table 1.5: World Economic Growth

Parameter	Point Est	Std Err
μ_G	0.0388	0.0028
ρ_G	0.4202	0.1242
σ_G	0.0119	0.0012

The results from estimating equation (1.22) are displayed in Table 1.5. The estimated mean growth rate for world output is 3.88%, and the estimated autocorrelation is 0.42. Both estimates are squarely within the range of estimates found from doing similar analysis at the country level. All parameters are estimated with a high degree of precision and are statistically significant at any standard level. With the estimated equation for world oil demand and the estimated law of motion for world output growth in hand, the model is now closed and can be brought into equilibrium to forecast future oil production and prices.

1.3.3 Equilibrium World Oil Production and Price Forecast

In order to forecast world oil production and prices into the future, 300 Monte Carlo simulations are preformed. The Monte Carlo simulations enable the forecast to capture three different types of uncertainty. The first type is uncertainty in the future productivity of oil exploration activity. Oil exploration over the next century could yield discoveries that are well above expectations or well below expectations. In the model presented in Section 1.2, this type of uncertainty is captured by the parameter σ_n, which is estimated at 0.1463, implying that the standard deviation in discovery outcomes around expectations is about 15%.

The second type of uncertainty that needs to be included is uncertainty in future world economic growth. Recent growth in the developing world, especially strong growth in China and India, has shown that above trend economic growth can quickly put strong pressure on the world oil markets, pushing up prices and the incentives to explore, develop, and produce oil. This type of uncertainty is captured by taking draws from the estimated AR(1) process for world economic growth displayed in equation (1.22), and feeding those growth rates into the demand for world oil estimated in equation (1.21).

The third source of uncertainty the Monte Carlo simulations account for is the uncertainty in the estimates of the model parameters displayed in Table 1.3. This form of uncertainty is captured by taking draws from the estimated joint distribution of the model parameters. The estimated variance-covariance matrix of the model parameters is listed in the appendix.

Before performing the Monte Carlo simulations, the price expectations for non-OPEC oil producers for the next 100 years need to be defined. One could continue to use the price expectations derived from the estimation of equation (1.15) in Section 1.2 using past real oil price data. Those parameter estimates are displayed in Table 1.1. However, in that case the expectations for future prices would not necessarily match the forecasted equilibrium prices generated by the model.

In order to ensure that price expectations used by the non-OPEC exploration, development and production managers are consistent with prices generated in equilibrium, the following strategy is employed. First, non-OPEC oil managers are assumed to continue to expect log real oil prices to follow the AR(1) process described in equation (1.15). Second, I iterate on the parameter values of equation (1.15) until the *a priori* price expectations match the realized equilibrium price forecast generated by the model. Hence, the equilibrium oil production and price forecasts are constructed as follows: (i) guess the parameter values, μ_p, ρ_p and σ_p, from equation (1.15), (ii) forecast equilibrium production and prices in 300 separate Monte Carlo simulations in order to account for uncertainty, (iii) estimate equation (1.15) on the forecasted prices, and (iv) update μ_p, ρ_p and σ_p until convergence is reached.

Quantitatively, both sets of price expectations generate similar results. The price expectations derived in Section 1.2 produce oil production forecasts that are slightly more peaked than price expectations that are consistent with the equilibrium price forecasts generated by the model.

1.3.4 Baseline Forecast: Constant OPEC Market Share

Figure 1.4 displays three forecasts of world oil production over the next 100 years: the EIA (2004) forecast, a forecast using methodology of Hubbert (1956), and the equilibrium production forecast generated by the model presented in this chapter. My baseline forecast is made under the assumption that OPEC continues to target its historic market share of 42% of world oil production. The constant OPEC market share and the structural model of non-OPEC production estimated in Section 1.2 combine to pin down the supply side of the world oil market. World oil supply is equated to world oil demand each period by adjusting the equilibrium world oil price.[6]

The single line, from 1900–2006, displays historic world oil production. In 2007, the line splits into three separate forecasts of world oil production. The dotted line labeled "EIA," displays the EIA's baseline scenario for peak world oil production. The EIA forecasts that world oil production will peak in the year 2037 at a production level of

[6] Note that in order to solve for the decision rules of the non-OPEC managers' problems it is necessary to have a discrete grid for oil prices. However, this means that markets will never perfectly clear since prices

53.2 billion bbl. The EIA forecast is based on a mean estimated total recoverable reserve level of 3 trillion bbl, a 2% production growth rate, and production decline thereafter, in which a constant reserve to production (RP) ratio of 10 is maintained. The mean forecast in this chapter is represented by a dashed line labeled "Mean," and it forecasts a peak production year of 2045 at a production level of 52 billion bbl. The production forecast in this chapter is strictly at odds with the production forecasts of those using the methodology of Hubbert (1956). Forecasts using the Hubbert model have predicted a peak in world oil production every year since 2000. The construction of the Hubbert forecast is presented in the appendix.

The main difference between the mean forecast in this chapter and the EIA forecast is the shape of the production path around the peak production year. In the EIA forecast, production growth does not slow at all as it approaches the peak production year. Hence, in the EIA forecast, the drop off in production after the peak production year is rather pronounced, due to the assumption of a fixed reserve base and the assumption of a constant RP ratio of 10 in post peak production years. In my model, production growth slows well before the peak production year. This is because the growth in the number of entrants into the oil industry necessary to satisfy equation (1.14) falls as cumulative discoveries increase.

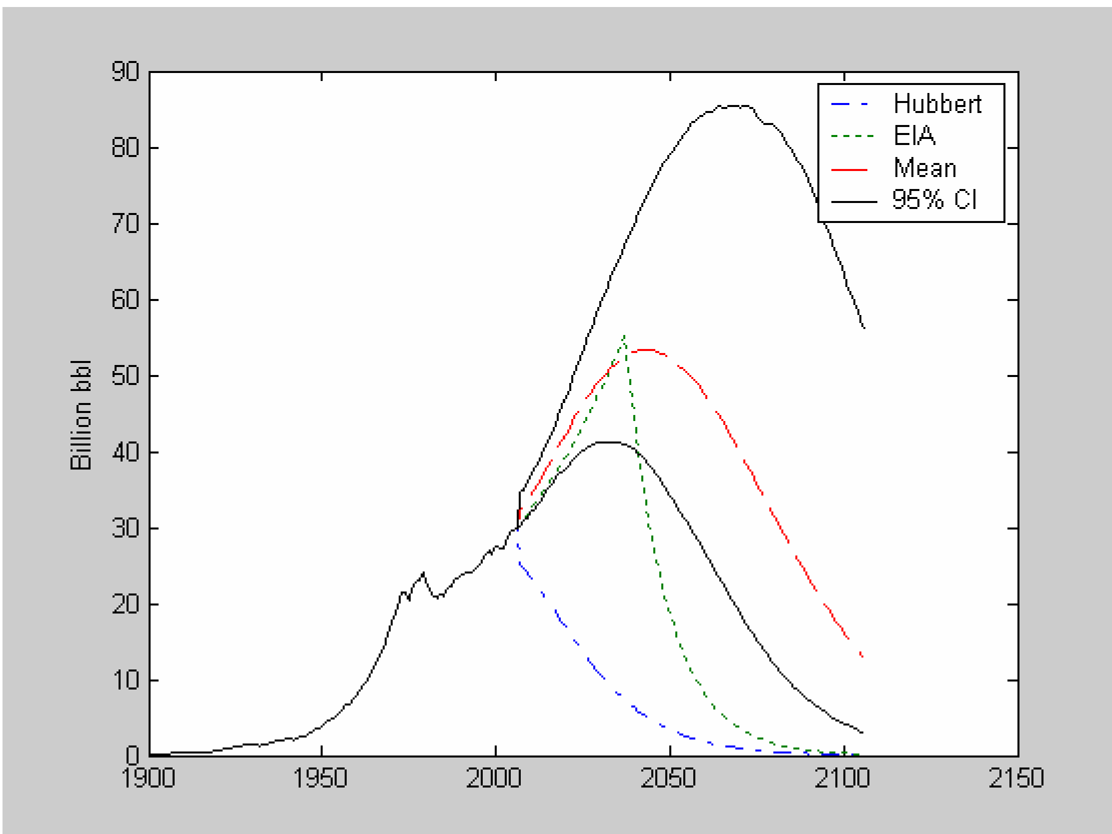
In essence, equation (1.14) combined with the parameter estimates for γ_0 and γ_1 imply increasing resource scarcity even though no explicit cap is imposed on total recoverable reserves. The slowing growth rate in world oil production also causes

---

are not continuous. Excess supply/demand can be brought arbitrarily close to zero by increasing the number of discrete points in the price grid but this has a high cost in terms of computational time.

equilibrium world oil prices to rise. Hence, production levels in the model stay above 50 billion barrels for nearly a decade after the peak production year, as higher prices counteract the forces of increasing resource scarcity. The 95% confidence interval implies that peak oil production, under a constant OPEC market share 42%, is likely to occur between the years 2033-2068 at a production level of 40.1 to 83.9 billion bbl.

Figure 1.4: World Oil Production Constant OPEC Market Share



As discussed in Section 1.1, the model presented in this chapter has no upperbound on total recoverable reserves. However, another implication of equation

(1.14), the estimated values for γ_0 and γ_1, and the estimated world demand for oil is that eventually equilibrium world oil production will begin to approach zero. Hence, an implied total recoverable reserve level can be calculated by simulating the model sufficiently far into the future. Under a constant OPEC market share scenario, the mean production forecast implies a total recoverable reserve level of 5 trillion bbl. This is almost two trillion more total recoverable reserves than the EIA's mean estimate of 3 trillion bbl and just over one trillion more reserves than the upperbound on the EIA's 95% confidence interval of 3.9 trillion bbl.

According to the EIA estimate, the 5 trillion bbl total recoverable reserve level implied by the model seems unreasonable high. This could reflect that OPEC's share of the world oil market is likely to decline over time or that the model parameters are biased towards an overly optimistic production forecast. Both the lower bound on the 95% confidence interval in the constant OPEC market share case and the mean forecast in the decreasing OPEC market share case imply a total recoverable reserve level within the EIA's range of estimates for total recoverable reserves. While either of these interpretations could be correct, it is important to note that the majority of the difference in total recoverable reserves between those implied by the mean production forecast in Figure 1.4 and the EIA estimate come after the year 2050. While geological estimates of total recoverable reserves try to explicitly account for technology growth, it is hard to forecast what future recovery rates will be in practice. The EIA (2004) assumes a recovery factor of about 50%. In other words, of the 6 trillion bbl of physical conventional oil present in the Earth's crust only 50% of those, or 3 trillion bbl, will be translated into recoverable oil reserves. The mean forecast in the constant OPEC market share case in this chapter implies a recovery factor of 83%.

Figure 1.5: Real Oil Prices Constant OPEC Market Share

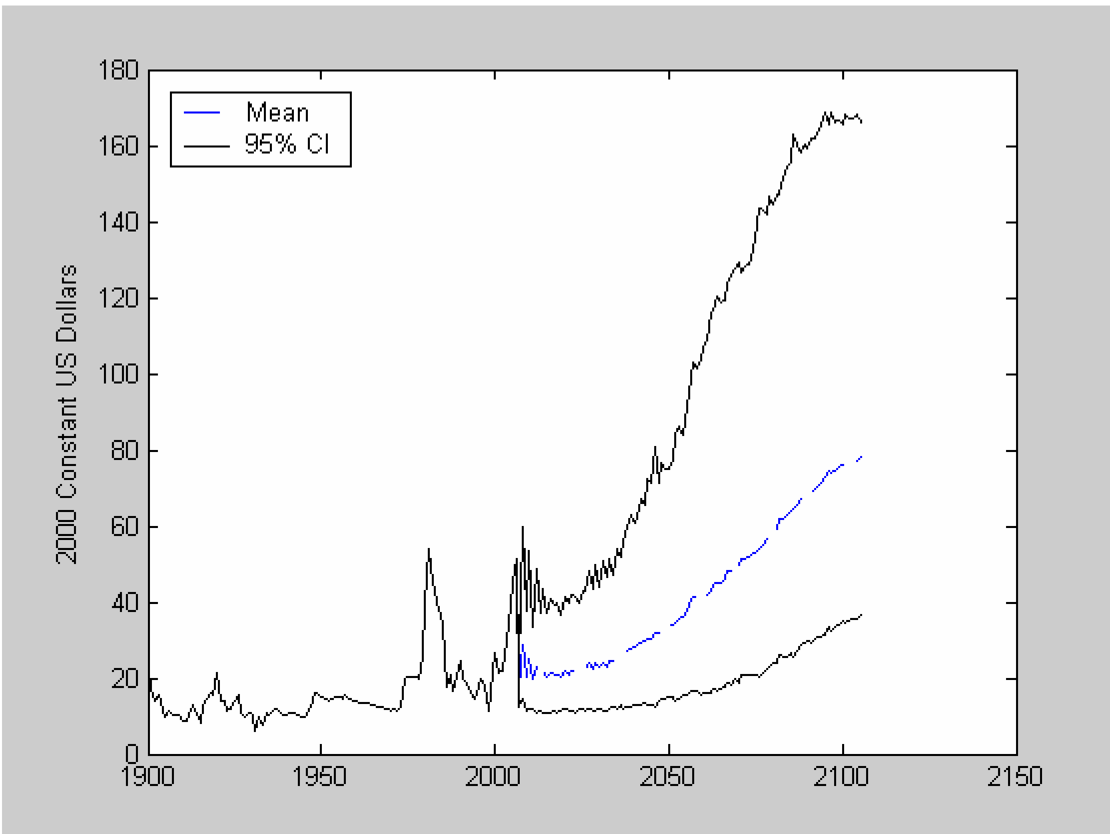


Figure 1.5 displays the model's forecast of world oil prices over the next 100 years. The single line, from 1900-2006, displays historic average annual real oil prices in constant 2000 dollars. The mean forecast calls for real oil prices to fall from their recent highs, to a level of about $25/bbl in constant 2000 dollars over the next decade. Under the mean forecast, real oil prices begin to rise slowly starting in about 2025. Real oil

prices continue to increase as world production peaks, before leveling off at a price of just over $80/bbl in constant 2000 dollars. If world oil production is at the low end of the model's forecast, then real oil prices can be expected to stay near current levels before increasing to a price of over $160/bbl over the next 100 years. However, if world oil production is at the high end of the model's forecast, then oil prices could return to the low levels seen in the late 1990s, with modest price increases only beginning after the year 2050.

1.3.5 World Oil Production and Price Forecast: Declining OPEC Market Share

Figure 1.6 displays the model's forecast of world oil production over the next 100 years under the assumption that OPEC's targeted market share decreases by 0.5% each year from its level of just under 42% in 2006. As in the baseline model, the declining OPEC market share and the structural model of non-OPEC oil production combine to make up the supply side of the world oil market. World oil supply is equated to world oil demand by adjusting the equilibrium world oil price.

With OPEC's market share of world oil production declining over time, the peak in world production occurs much faster and at a lower level. The mean forecast is for world oil production to peak in the year 2035 at an annual production level of just over 45 billion bbl. As in the baseline forecast, the oil production level around the peak production year is relatively flat. Hence, even if the peak in world oil production is only a few decades away, markets will have close to two decades to adjust to stagnating oil production growth before oil output begins to significantly decline. The 95% confidence interval places the peak in world oil production between the years 2029-2058, at annual production level of 37 to 63.3 billion bbl.

Figure 1.6: World Oil Production Decreasing OPEC Market Share

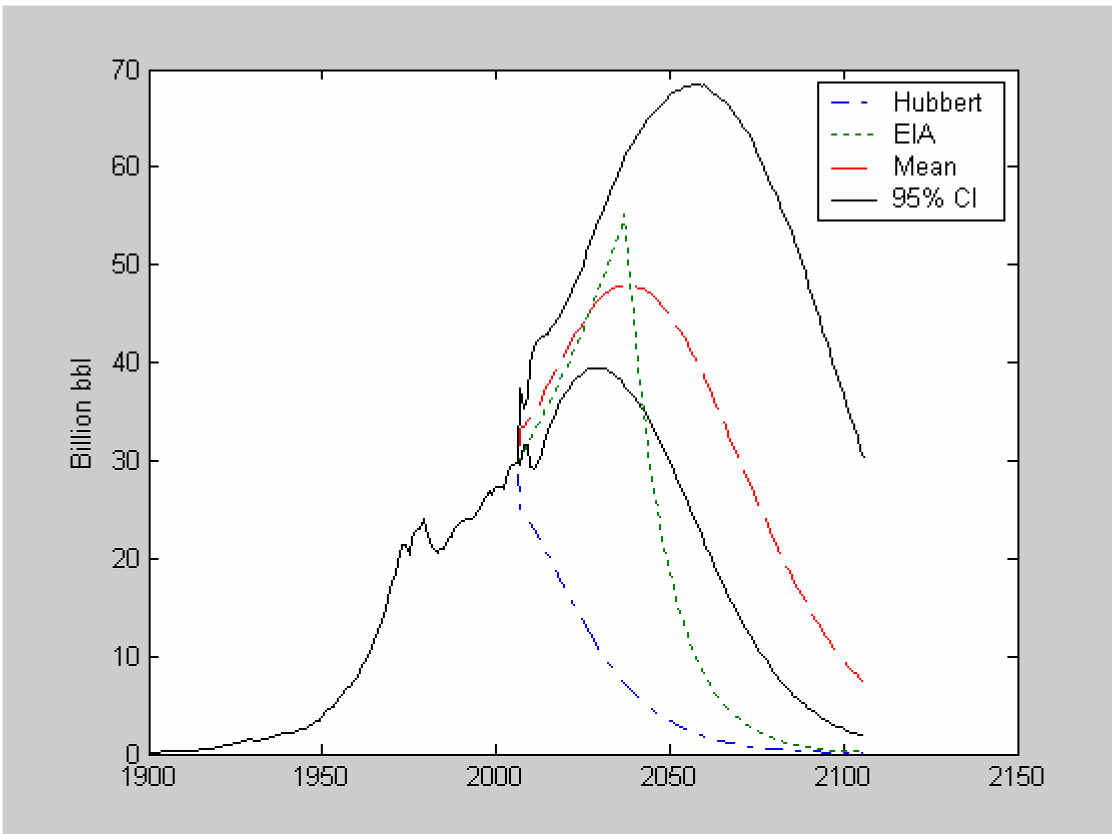
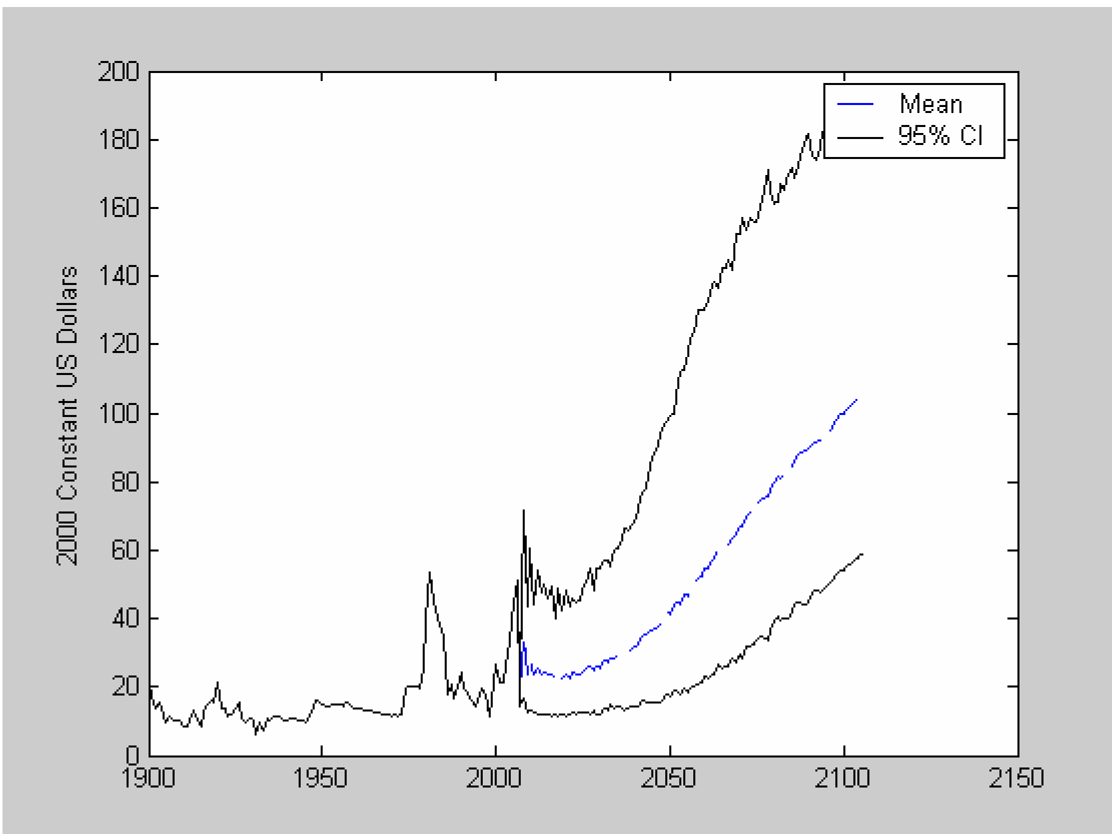


Figure 1.7 displays the mean price forecast in the case where OPEC's share of the world oil market declines by 0.5% each year. The mean price forecast in this case is little changed from the price forecast in the constant OPEC market share case. Mean prices in the declining OPEC market share case are still expected to fall from their recent highs to a real price of around $26/bbl in 2000 constant dollars. Mean prices in the declining

OPEC market share case rise sooner and slightly faster than in the constant OPEC market share case. However, relative to the year-to-year volatility in real oil prices, this difference in mean oil prices would hardly be perceptible. The primary reason for the similarity in the price forecasts, even with the strong difference in the production forecast, is the relatively stable production around the peak production year.

Figure 1.7: Real Oil Prices Decreasing OPEC Market Share



As discussed earlier, an examination of equation (1.14) shows that as cumulative discoveries rise over time the growth in the equilibrium number of non-OPEC entrants into the oil industry, N_e, begins to slow. The slowing growth in N_e first causes oil exploration to slow, and then causes oil development and production to slow. With oil production slowing, equilibrium prices must rise to offset the increased demand for oil caused by world economic growth. Rising oil prices also increase the value of drilled and undrilled wells, counteracting the effects of increasing cumulative discoveries and stabilizing the equilibrium number of entrants. Hence, the equilibrium effects of rising prices cause world oil supply and demand to essentially flat line around the peak production year. Thus, the mean price forecast for future world oil prices is little changed by the timing and level of oil output in the peak production year.

1.3.6 World Oil Production and Price Forecast: Increasing OPEC Market Share

Figure 1.8 displays the forecast for world oil production over the next 100 years under the assumption that OPEC's targeted market share increases by 0.5% each year. As in the previous two forecasts, the increasing OPEC market share and the structural model of non-OPEC oil production combine to make up the supply side of the world oil market. World oil supply is equated to world oil demand by adjusting the equilibrium world oil price.

As expected, with OPEC's market share of world oil production increasing over time, the peak in world production occurs at a later date and at a higher level. The mean forecast is for world oil production to peak in the year 2053 at an annual production level of just under 63.6 billion bbl. As in the previous two forecasts, the oil production level around the peak production year is relatively flat. Production in the increasing OPEC market share scenario implies 26 years of production in excess of 60 billion bbl. The 95% confidence interval places the peak in world oil production between the years 2039-2082, and at annual production level of 46.6 to 114.6 billion bbl.

Figure 1.8: World Oil Production Increasing OPEC Market Share

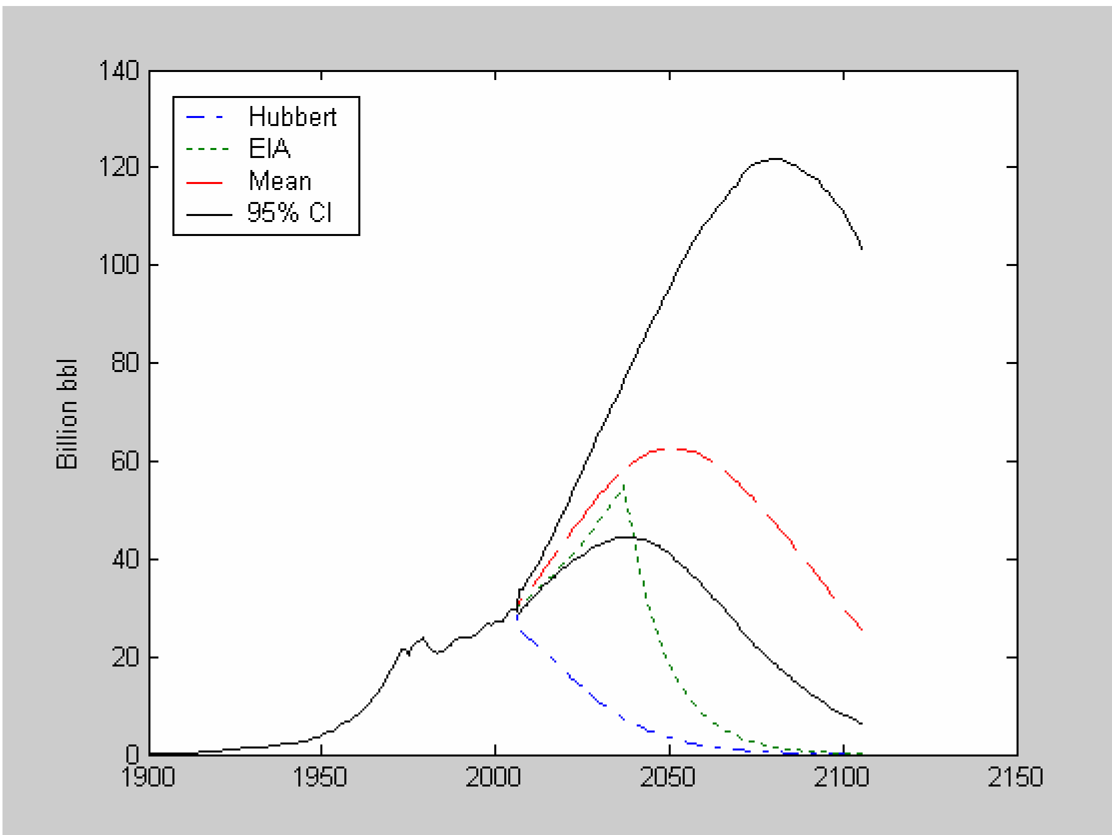
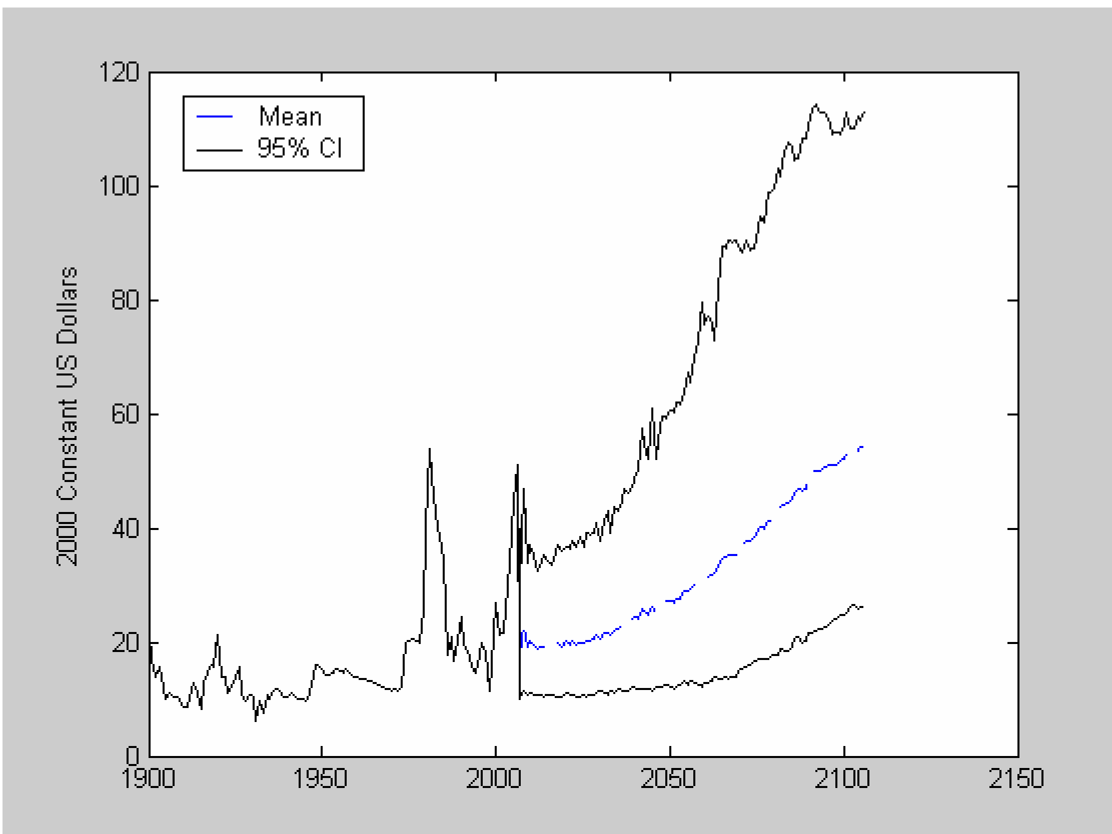


Figure 1.9 displays the mean price forecast in the case where OPEC's share of the world oil market increases by 0.5% each year. The mean price forecast in the case of increasing OPEC market share, is little changed from either the constant or decreasing OPEC market share forecast. Prices are still expected to fall from their recent high to a

real price of around $22.5/bbl in 2000 constant dollars. Mean prices in the declining OPEC market share case rise later and more slowly than in the baseline scenario but, as noted early, relative to the year-to-year price fluctuations, this difference is not economically significant. In the case of increasing OPEC market share, mean prices are forecasted to level out towards the end of the century at a real price of $65/bbl in constant 2000 dollars.

Figure 1.9: Real Oil Prices Increasing OPEC Market Share



1.4 CONCLUSION AND SUGGESTIONS FOR FURTHER RESEARCH

This chapter presents a structural model of a competitive oil industry in which exploration, development and production are all explicitly modeled. The model is then brought to the data on non-OPEC oil production, reserves and discoveries over the period 1980-2006. The model is estimated by simulated method of moments (SMM) and is found to match the moments of the data quite well. In-sample simulations of the model also match the time series on non-OPEC production and reserves. The structural model of non-OPEC oil production is then combined with different targeted market shares for OPEC oil production to make up the supply side of the world oil market. The supply side of the world oil market is then brought into equilibrium with an estimated world demand for oil. The resulting equilibrium world oil production and price levels are then simulated forward in numerous Monte Carlo simulations. The Monte Carlo simulations enable the model's forecasts to account for uncertainty about world output growth, future oil discoveries, and the model parameters.

In my model's baseline case, in which OPEC continues to target its historic market share of 42% of the world oil market, I find that world oil production is likely to peak in the year 2047 at a yearly production level of 52 billion bbl. This production forecast is similar to the EIA (2004) forecast that puts peak world oil production at 53.2 billion bbl in the year 2037. The main difference between the results in this chapter and the results from the EIA (2004) is the relative stability of world oil output around the peak production year. In this model, the forces of increasing resource scarcity and rising world oil prices offset one another to produce nearly two decades of world oil production at just over 50 billion bbl. My results are at strict odds with studies using the methodology of Hubbert (1956) that predict impending world oil shortages.

This chapter also forecasts that real oil prices are likely to fall below $30/bbl in constant 2000 dollars within the next decade. However, real prices are likely to gradually rise after 2025 approaching $85/bbl by the end of the century. To the best of my knowledge this is the first research piece to use a structural model of world oil production to forecast equilibrium world oil prices into the future. Hence, the equilibrium prices in this model are determined by supply responses that are governed by the deep parameters of oil exploration, development and production rather than reduced form estimates based on historical relationships between prices and other variables.

Two future avenues of research seem particularly appropriate. The first is to extend the data on world oil reserves back in time. The data in this chapter come from the BP Statistical Review (2007) and only contain reserve data back to 1980. The EIA has reserve data for the US stretching back to 1899, and it is likely that longer time series for most of the world's oil producers could be constructed on a country-by-country basis. Those national level statistics could then be summed up to the desired level of aggregation. A second avenue of future research is to endogenize OPEC's share of the world oil market. However, modeling the fully specified non-cooperative game that OPEC and non-OPEC oil producers and consumers play with one another is a daunting task. Nonetheless, a more sophisticated reduced form method of incorporating OPEC into the world oil market seems to be an attractive alternative and an important extension of the work presented here.

Since oil is likely the most important commodity to the world economy, forecasts of future of world oil production and prices have drawn rightful attention from policy makers and private individuals alike. This chapter finds that while conventional oil production will likely peak sometime around the middle of this century, the peak in world oil production will be accompanied by nearly two decades of essential flat production. The equilibrium effects of gradually rising real oil prices result in slowing oil demand growth and increased incentives to explore, develop, and produce oil—thus preventing large declines in world oil production and dramatic oil price spikes. This chapter finds that impending cataclysmic shortages in world oil production are, in essence, a near zero probability event.

Chapter 2: Do Ethnic Differences Inhibit the Provision of Environmental Public Goods?

One of the most important services a government can render is the provision of public goods. Due to its non-excludable and non-rival nature, environmental quality is often cited as a classic example of a public good. If certain country-specific factors are impediments to good government, then across countries we would expect to find a strong correlation between those factors and public good provision. Some suggest that ethnic divisions within a country are such a factor and can result in the poor provision of public goods. This chapter finds that ethnic fractionalization, a measure of ethnic diversity, is significantly and positively correlated with country-level emissions of carbon dioxide, chlorofluorocarbon (CFC), methane, carbon monoxide, sulfur dioxide emissions, and hazardous waste. Ethnic fractionalization is also significantly and positively correlated with higher local levels of ambient biochemical oxygen demand (BOD). Moreover, the estimated coefficients suggest that ethnic fractionalization has a large degree of economic significance as well. According to my point estimates, a one standard deviation increase in ethnic fractionalization increases country-level emissions by an average of 19%. Ethnic fractionalization appears to hamper significantly the provision of environmental quality, and it is therefore likely a substantial obstacle to the formation of well functioning institutions.

A growing literature has found that ethnic fractionalization inhibits economic growth and impedes the development of effective institutions. Empirical results on this subject have been compelling, but not without qualifications. In the growth literature, papers such as La Porta et al. (1999) and Alesina et al. (2003) find that ethnic fractionalization is inversely correlated with economic growth. However, these authors also find that other explanatory variables such as latitude and legal origin appear to be just as important as ethnic fractionalization in explaining cross-country growth rates. Alesina et al. (2003) finds that, under most specifications, controlling for latitude causes the coefficient on the ethnic fractionalization variable to lose its statistical significance. Alesina et al. (1999) find that, for US cities, shares of government spending are negatively correlated with ethnic fractionalization for education, roads, welfare, sewers and trash. However, they also find that ethnic fractionalization is positively correlated with the share of spending devoted to police and health, both of which could be considered public goods as well. This chapter extends this analysis to another public good, environmental quality.

In the environmental justice literature, a number of empirical papers show that minority communities have higher levels of exposure to many common pollutants. Brooks and Sethi (1997) analyze US data on exposure to air toxics from 1988-1992 and find that "a 1% greater proportion of this subpopulation [African Americans] in a zip code area is, on average, correlated with a value of exposure that is 2.8% larger" (P. 245). Brajer and Hall (2005) find that in the South Coast Air Basin of California particulate pollution is positively correlated with the percentage of African American and Hispanic residents in the area.

The purpose of this chapter is to test the hypothesis that ethnic divisions impair public good provision by looking at the statistical relationship between measures of pollution and cross-country measures of ethnic fractionalization. If ethnic fractionalization truly does impair public good provision, then controlling for other variables should not cause bias in the estimation. This chapter develops a theoretical model based on the work of Alesina et al. (1999) to motivate the statistical model and then conducts an empirical analysis for eight common pollutants.

This chapter makes three contributions to the literature. First, it extends the ethnic fractionalization literature on growth, and certain public goods like education, to consider environmental quality. In many of the specifications in Alesina et al. (2003), their ethnic fractionalization variable loses statistical significance once latitude and legal origin are included. For some, this might call into question the importance that ethnic fractionalization plays in shaping institutions. Here, however, even after controlling for latitude and legal origin, ethnic fractionalization still has a statistically and economically significant affect on all but one of the pollutants studied.

The second contribution this chapter makes is to measure ethnic fractionalization's effect on the actual level of public good provision. Other empirical papers focus on ethnic fractionalization's effect on the share of spending on public goods or on indexes of public good quality. In contrast, the statistical work in this chapter uses either ambient pollution levels, which are exact measures of public good provision or emissions levels, which in most cases are near approximations of public good provision.

The third contribution of this chapter is to extend the environmental justice literature to look at political economy explanations for the observed patterns in the data. The environmental justice literature has long recognized the statistical correlation in the US between pollution levels and the presence of minority populations. This empirical finding has been interpreted by some to be evidence of environmental injustice. Along similar lines, the growth and political economy literature has focused on ethnic conflict and its effect on the quality of institutions. Empirical papers in this literature find an inverse correlation between ethnic fractionalization and the provision of public goods like education. Since this chapter uses measures of ethnic fractionalization at the country level, my empirical findings suggest that elevated pollution levels in ethnically diverse countries may not be due to targeted environmental injustice, but may instead be the result of an inability to reach a consensus on the shape and form of public good provision.

This chapter finds that ethnic fractionalization is positively correlated with higher emissions of carbon dioxide, CFCs, methane, carbon monoxide, sulfur dioxide, and ambient levels of biochemical oxygen demand. Ethnic fractionalization has a statistically insignificant effect on nitrogen oxide emissions even though the unconditional correlation is quite large. Under a number of specifications coefficients on latitude and legal origin are statistically significant. However, the sign of these coefficients switch back and forth depending on the pollutant making it difficult to argue that the relationship is not spurious. In addition, unlike the results in the growth literature, controlling for latitude and legal origin has almost no impact on ethnic fractionalization's estimated economic or statistical significance.

This chapter is organized as follows. The Section 2.1 presents a theoretical model to motivate the statistical analysis. Section 2.2 presents the statistical model, the data and equation structures. Section 2.3 presents the main results of the chapter by looking at the relationship between ethnic fractionalization and country-level pollution emissions. Section 2.4 performs a robustness check of the results in Section 2.3 by looking at ambient environmental quality from the local level. Finally, Section 2.5 concludes the chapter.

2.1 THEORETICAL MODEL

The model presented here is a close variant of the model presented in Alesina et al. (1999). The model consists of J countries, each with a continuum of citizens from 0 to 1. The citizens in each country have to decide on the level of public good provision, g, and the type of public good provision, t. The type of public good provision, t, is assumed to lie on a one dimensional ideological line. Decisions in each country are made by majority rule. Citizen i in country j has the following utility function:

$$(2.1) \quad u_{ij} = \frac{g_j^{\alpha}}{\alpha}(1 - | t_j - t_{ij} |) + c_j$$

where in country j, u_{ij} is the utility of citizen i, c_j is private consumption, g_j is the level of public good provision, t_j is the type of public good currently provided in country j, and t_{ij} is the type of public good preferred by individual i. The parameter α is constrained to take on values such that $\alpha \in (0,1)$. The bounds on α indicate that the marginal utility of the public good is decreasing.

Private consumption in country j is determined by the following budget constraint:

$$(2.2) \quad c_j = y_j - \tau_j ,$$

where y_j is the income endowment common to all individuals in country j and τ_j is the lump sum tax common to all individuals in country j. The government in country j must run a balanced budget. Hence, the government budget constraint is the following:

(2.3) $\tau_j = p(X_j)g_j$,

where $p(X_j)$ is the cost of providing one unit of the public good, and X_j is a vector of variables. The variables that compose the vector X_j are common to all countries; however, the values of those variables are not. The function p converts the vector X_j into a country-specific price of public good provision that is known to all citizens.

If individual i in country j were allowed to choose the level of public good provision taking t_j as given, then the following equation would describe their optimal choice:

(2.4) $g_{ij}^* = [(1-|t_j - t_{ij}|)/p(X_j)]^{1/(1-\alpha)}$.

To derive equation (2.4) substitute equations (2.3) and (2.2) into equation (2.1), take the derivative of equation (2.1) with respect to g_j, set it equal to zero, and then solve for individual i's preferred level of public good provision, g_{ij}. Following Alesina et al. (1999), it is assumed that citizens of country j first vote on the size of the public good, g_j, and then on the type of the public good, t_j. In the case of providing a public good like environmental quality, the decision over t_j will most likely be a question about abatement. Citizens are likely to disagree over what abatement technologies to use and most importantly the division of total abatement among individuals. Given the two-stage nature of the voting process, citizen i knows that when he or she votes on the size of the public good, the type of the public good will be decided by the median voter in the second stage of the voting process.

Let us now define $\hat{d}_{ij} = |t_j^m - t_{ij}|$. Here, $\hat{d}_{ij}$ is the distance between the type of public good preferred by citizen i in country j, t_{ij}, and the type of public good preferred by the median voter in stage two of the voting process, t_j^m. In equilibrium, the size of the public good, g_j, is determined in stage one of the voting process by the median distance from the median voter in stage two. Hence, by defining d_j^m as the median of $\hat{d}_{ij}$ and inserting it into equation (2.3) the following equilibrium size of the public good is derived:

(2.5) $\quad g_j^e = [(1-d_j^m)/p(X_j)]^{1/(1-\alpha)}$.

As can be seen from equation (2.5), the equilibrium size of public good provision in country j is just a function of variables specific to that country. Equation (2.5) also implies that the size of the public good is decreasing in d_j^m.

Define $t_j(N)$ as the type of public good provision preferred by the N^{th} percentile of the distribution of t_{ij}. I now introduce the notion of a strict, median-preserving spread in the distribution of t_{ij}. The distribution of t_{ik} represents a strict, median-preserving spread of the distribution of t_{ij} if the following are true: (i) $t_j(50) = t_k(50)$, and (ii) $|t_j(50) - t_j(N)| < |t_k(50) - t_k(N)|$ for all N not equal to 50.

Proposition 1. If the distribution of t_{ik} is a strict median preserving spread of the distribution of t_{ij}, then $g_j^e > g_k^e$.

Proof. Given the definition of $t_j(N)$, the type of public good provision preferred by the median voter in country j is $t_j(50)$. Hence, $\hat{d}_{ij}$ is equal to $|t_j(50) - t_j(N)|$ when N is equal to the percentile corresponding to agent i's location in the distribution of t_{ij}.

By definition of a strict, median-preserving spread $|t_j(50) - t_j(N)| < |t_k(50) - t_k(N)|$ for all N not equal to 50. Thus, it must be the case that $d_j^m < d_k^m$, since d_j^m and d_k^m are just the medians of $\hat{d}_{ij}$ and $\hat{d}_{ik}$ respectively. Therefore, $g_j^e > g_k^e$ since from equation (2.5) g_j^e is clearly decreasing in d_j^m and as shown above $d_j^m < d_k^m$.

From the above proposition it is clear that a strict, median-preserving-spread of the distribution of t_{ij} results in a smaller size of public good provision. If increasing ethnic fractionalization causes a strict, median-preserving spread in the preferred types of public good provision, then countries with higher levels of ethnic fractionalization will have a level public good provision that is lower in size than countries with less ethnic fractionalization. Hence, it is the assumption that ethnic fractionalization does in fact produce a spread in the distribution of t_{ij} that provides the theoretical foundation for an inverse relationship between ethnic fractionalization and country level public good provision. Empirical tests are now needed to determine if such relationship exists in the data.

2.2 STATISTICAL MODEL

The previous section uses a theory model to derive equation (2.5), which relates the size of public good provision in country j to the median distance from the type of public good preferred by the median voter, d_j^m, and the price of public good provision, $p(X_j)$. Taking the natural log of both sides of equation (2.5) yields:

(2.6) $\ln(g_j^e) = \frac{1}{1-\alpha}\ln(1-d_j^m) - \frac{1}{1-\alpha}\ln(p(X_j))$.

In theory, with perfect knowledge of each country's $p(X_j)$ and d_j^m, equation (2.6) could be directly estimated. Unfortunately, such perfect knowledge is not available and thus reduced form modeling assumptions are needed in order to estimate the relationship between public good provision and other explanatory variables.

2.2.1 Equation Structure

In order to proceed with the statistical analysis of this chapter, three modeling assumptions have been made. First, it is assumed that ethnic fractionalization's affect on d_j^m, through its affect on the distribution of t_{ij}, can be approximated by the following reduced form relationship:

(2.7) $\ln(1-d_j^m) = \gamma_0 ethfrac_j$.

Second, p is assumed to be multiplicative function of the vector of variables X_j such that $p(X_j) = x_{1j}^{-\gamma_1} \cdot x_{2j}^{-\gamma_2} \cdot \ldots \cdot x_{Nj}^{-\gamma_N}$ and $\gamma_1, \gamma_2, \ldots, \gamma_N$ can be either positive or negative parameters. From this second assumption it is easy to show the following:

(2.8) $\ln(p(X_j)) = -\gamma_1 \ln(x_{1j}) - \gamma_2 \ln(x_{2j}) - \ldots - \gamma_N \ln(x_{Nj})$.

And third, the vector of variables, X_j, that influence the size of the public good are assumed to be GDP, GDP squared, the percentage of GDP that comes from manufacturing, the percentage of GDP that comes from agriculture, population density, land area, year, latitude, and legal origin. Substituting these three modeling assumptions into equation (2.6) results in the following equation structure:

$$
\begin{aligned}
&\ln(g_j^e) = \\
(2.9) \quad &\beta_0 ethfrac_j + \beta_1 \ln(gdp_j) + \beta_2 \ln(gdp_j)^2 + \beta_3 manfact_j + \beta_4 agrclt_j \\
&+ \beta_5 \ln(popden_j) + \beta_6 \ln(land_j) + \beta_7 lat_j + \beta_8 \ln(t) + legal_j D + C
\end{aligned}
$$

where $\beta_k = \gamma_k /(1-\alpha)$, for $k = 0,...,8$ and where g_j^e is the public good provision in country j, gdp_j is per capita gross domestic product in country j, $popden_j$ is the population density in country j, $land_j$ is the land area of country j, $agrclt_j$ is the percentage of gdp_j that comes from agriculture, $manfact_j$ is the percentage of gdp_j that comes from manufacturing, lat_j is the latitude of country j, $ethfrac_j$ is the level of ethnic fractionalization in country j, t is the year of the observation, D is a vector of coefficients, and $legal_j$ is a matrix of dummy variables that indicate whether country j is of French, German, Socialist or Scandinavian legal origin. The English legal origin dummy variable has been left out in order to accommodate the constant term C. Thus all of the legal origin coefficients should be interpreted relative to the baseline of being of English legal origin.

The motivation for the equation structure comes from two sources. First, in order to be consistent with prior literature much of the specification has been chosen to match that of La Porta et al. (1999) and Alesina et al. (2003). Specifically the following variables were all included as regressors in their empirical work: log per capita GDP, log per capita GDP squared, latitude, legal origin and ethnic fractionalization. The inclusion of these variables allows us to compare their empirical work with my analysis of environmental public good determination in order to better understand the relative importance of ethnic fractionalization, latitude and legal origin.

Second, according to the theory outlined in Section 2.1, an important determinant of ambient environmental quality is the function $p(X_j)$. This function is meant to generically capture all of the costs of providing environmental amenities in a particular country. In order to control for cross-country heterogeneity in the costs of providing environmental amenities, I include the variables of $agrclt_j$, $manfact_j$, $land_j$ and t. While a number of variables are likely to influence the costs and benefits of environmental public good provision, it is of particular importance to control for the composition of GDP and the physical size of the country in which pollution can attenuate over. It is also important to control for technological advancements over time and hence, these variables are included in the analysis here.

The dependent variable in equation (2.9) is the log level of environmental quality. Unfortunately, the level of environmental quality provided in each country is not known. In practice, environmental quality is often approximated by measures of emissions or by pollutant levels per volume of air or water. Thus due to data limitation equation (2.9) cannot be estimated. Instead, most of the estimated equations take per capita emission levels as the dependent variable in place of the unknown level environmental quality. In addition, emissions data set used in this chapter covers a number of years as well as countries. Hence, the econometric model to be estimated in this chapter is the following:

$$\begin{aligned} &\ln(e_{jt}) = \\ (2.10)\quad &\beta_0 ethfrac_j + \beta_1 \ln(gdp_{jt}) + \beta_2 \ln(gdp_{jt})^2 + \beta_3 manfact_{jt} + \beta_4 agrclt_{jt} \\ &+ \beta_5 \ln(popden_{jt}) + \beta_6 \ln(land_j) + \beta_7 lat_j + \beta_8 \ln(t) + legal_j D + C + \xi_{jt} \end{aligned}$$

where e_{jt} is the level of per capita emissions in country j in year t.

2.2.2 The Data

A variety of sources were employed in order to construct the data set used in this chapter. Real gross domestic product data is from the 2005 World Bank Development Indicators. This data set covers the years 1960-2003 and the units are measured in constant 2000 US dollars. Data on the percentage of real GDP that comes from manufacturing and agriculture are from the 2002 World Bank Development Indicators (WBDI) and covers the years 1960-2000. Population density data is from World Population Prospects: The 2002 Revision provided by the United Nations Population Division/Department of Economics and Social Affairs (UNDESA). Population density is measured by people per square kilometer and cover the years 1961-2002. Land area data is from FAO STAT 2004 provided by the Food and Agriculture Organization of the UN and covers the years 1961-2002. Country latitude data is from the 2006 CIA World Factbook and legal origin data is from La Porta et al. (1999).

The measures of country-level ethnic fractionalization come from Alesina et al. (2003). The measures Alesina et al. (2003) use capture the probability that two randomly selected people from country j belong to the same ethnic group. Ethnic fractionalization is calculated according the following formula:

$$(2.11) \quad ethfrac_j = 1 - \sum_{i=1}^{N} s_{ij}^2 ,$$

where s_{ij} is the percentage of the population of country j that is of ethnicity i. Thus a country with perfect ethnic homogeneity has an $ethfrac$ equal to zero and a country with perfect ethnic heterogeneity has an $ethfrac$ equal to one.

Table 2.1: Cross-Country Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
LHS Variables:					
CO_2	2409	3.0888	4.6906	0.005	35.7526
CO	265	0.2646	0.352	0.0022	2.8958
CH_4	611	0.0646	0.0663	0.0047	0.5557
CFC	1421	0.0956	0.4513	0	6.8125
BOD	1371	5.6952	4.7402	0.0097	27.2457
SO_2	265	0.0253	0.0446	0.0004	0.5256
NO_2	612	0.0031	0.0046	0.000004	0.0664
Hazardous Waste	115	0.0001	0.0001	1.84E-05	0.0011
RHS Variables:					
GDP	2677	4063.509	6757.567	86.08805	47746.07
Popden	2677	145.7977	480.3403	1.2354	6584.328
Land	2677	75500.9	172076.8	18	932745
Agriclt	2677	0.2048	0.1492	0.0014	0.7176
Manfact	2677	0.1509	0.078	0.0019	0.4354
Ethfrac	2677	0.4521	0.2636	0	0.9302
Lat	2677	0.2393	0.1725	0	0.7222
Legal Origin:					
English	2677	0.3874	0.4872	0	1
French	2677	0.4733	0.4994	0	1
German	2677	0.0202	0.1406	0	1
Scand	2677	0.0269	0.1618	0	1
Socialist	2677	0.0923	0.2895	0	1

GDP and emissions data all in per capita units.

Summary statistics for RHS variables calculated over all observations for which some emissions data are available.

The country level data described above was then matched with country level emissions data. Data on carbon dioxide emissions, measured in metric tons per person, is from the UN Framework Convention on Climate Change (UNFCCC) and UNDESA and covers the years 1980-2001. BOD emissions data, measured in kilograms per day, is from the 2002 WBDI and covers the years 1980-1999. Carbon monoxide and sulfur dioxide emissions data, measured in thousands of metric tons, is from the Emission Database for Global Atmospheric Research (EDGAR 3.2) and covers the years 1990 and 1995. Methane and nitrogen dioxide data, measured in thousands of metric tons, is from

EDGAR 3.2 and covers the years 1970, 1975, 1980, 1985, 1990 and 1995. CFCs emissions data, measured in ozone depleting potential metric tons, is from the UN Environment Program Ozone Secretariat and covers the years 1986 and 1989-2003. Hazardous waste emissions data, measured in thousands of tons, is from the 2004 OECD Environmental Data Compendium and covers the years 1990-2002.

The dependent variable for the majority of the estimated equations is country-level per capita emissions. For pollutants such as carbon monoxide, the correlations between country-level emissions and country-level ambient air quality are likely to be high-- due to the limited role of transboundary spillovers. For pollutants such as sulfur dioxide, however, the divergence between country-level emissions and country-level ambient air quality is country-specific. In the US, for instance, the majority of sulfur dioxide released in the Rust Belt of the US lands on cities in the northeastern US. Thus for the US, sulfur dioxide emissions are a close approximation of ambient environmental quality. However, in Europe transboundary sulfur dioxide spillovers are significant and play an important role in determining environmental quality. Unfortunately, data that matches sulfur dioxide emission in one country to acid rainfall in another is limited to a small number of countries. Thus, in order to cover a larger sample of countries, most of the analysis in this chapter uses emissions data.

The majority of the statistical work in this chapter is done at the national level, but some statistical analysis is carried out at the local level as a robustness check. For the empirical work done at the local level, I use a data set kindly provided to me by Hilary Sigman. Her data set contains information, on among other things, ambient water quality as measured by levels of biochemical oxygen demand in a number of rivers around the world and was the basis for her 2004 paper. This data set is discussed in more detail in Section 2.4 of the chapter when the robustness check is preformed.

2.3 THE RESULTS

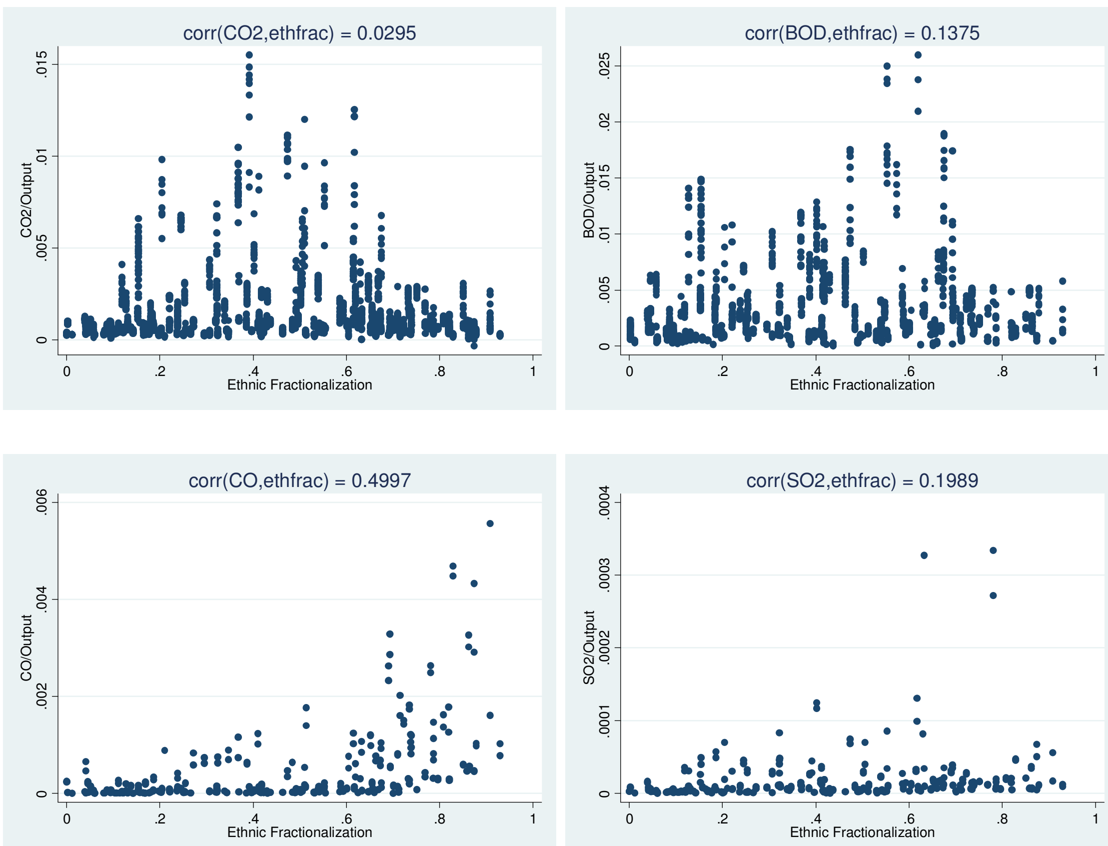
Before discussing the estimated coefficients from the fully specified model in equation (2.10), it important to examine the unconditional correlations between ethnic fractionalization and emissions. Strong unconditional correlations reduce the likelihood that economically and statistically significant *ethfrac* coefficient estimates are the result of model specification bias in equation (2.10).

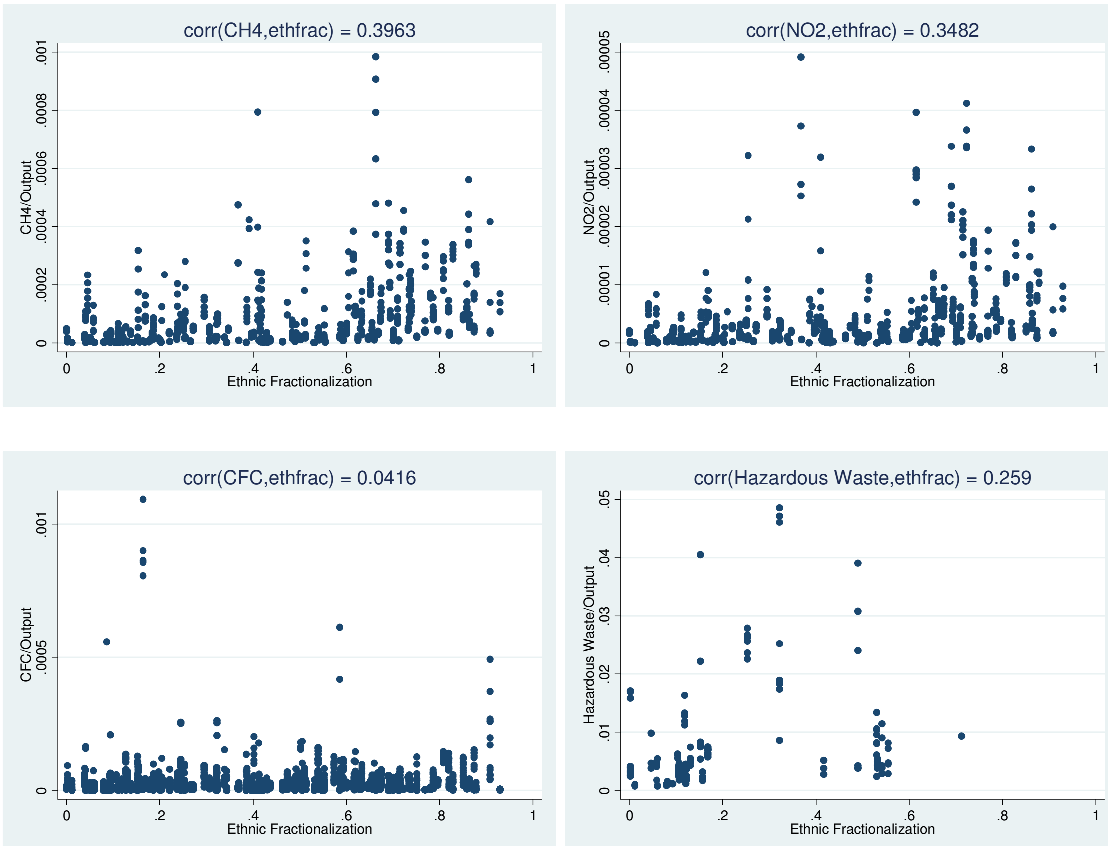
2.3.1 Unconditional Correlations

Figure 2.1 plots each country's emissions per unit of output against that country's level of ethnic fractionalization. Listed at the top of each graph is the unconditional correlation between ethnic fractionalization and emissions per unit of output.

A pronounced uptrend is evident in almost all of the scatter plots. Country level emissions per unit of output fan out and tend to increase as country level ethnic fractionalization increases. Excluding carbon dioxide and CFCs, the unconditional correlations between ethnic fractionalization and emissions per unit of output are all quite high: ranging from 0.1375 for BOD to 0.4997 for carbon monoxide. The strong unconditional correlation between ethnic fractionalization and emissions per unit of output make it likely that ethnic fractionalization plays some roll in public good provision. However, in order to quantify ethnic fractionalization's effect on emissions and ensure that the unconditional correlations are robust to multiple controls, regression analysis is needed.

Figure 2.1: Emissions and Ethnic Fractionalization





2.3.2 Regression Results

In the Table 2.2 below, each row represents a different estimated equation. The estimated equations are indexed by the particular pollutant that is studied, and that pollutant appears in the first column of Table 2.2. The remaining columns show the estimated coefficients on the legal-origin dummy variables, latitude, and ethnic fractionalization. The standard errors appear in parentheses. For brevity, the estimated coefficients for the other regressors discussed in Section 2.1 are not reported here in

Table 2.2, but they are available upon request. All of the coefficients in Table 2.2 are estimated using ordinary least squares.

Table 2.2: Determinants of Cross-Country Emissions

Pollutant	French	German	Scand	Socialist	Latitude	Ethfrac	R^2	Obs.
CO_2	-0.287***	-0.342***	-0.297**	0.986***	0.801***	0.652***	0.84	2409
	(0.031)	(0.106)	(0.127)	(0.065)	(0.132)	(0.069)		
BOD	-0.430***	-0.345***	0.223**	0.242***	0.468***	-0.066	0.75	1371
	(.034)	(0.090)	(0.088)	(0.075)	(0.133)	(0.081)		
CH_4	-0.235***	-0.463***	-0.770***	0.202*	-0.273	0.230**	0.58	611
	(0.045)	(0.165)	(0.151)	(0.114)	(0.198)	(0.106)		
CO	-0.044	-0.064	-0.211	0.048	-1.866***	0.660***	0.59	265
	(0.090)	(0.274)	(0.276)	(0.181)	(0.375)	(0.201)		
NO_2	-0.061	-0.698***	-0.513***	-0.618***	0.872***	-0.0555	0.49	612
	(0.059)	(0.216)	(0.197)	(0.149)	(0.257)	(0.139)		
SO_2	-0.106	-0.326	-0.374	0.613***	1.334***	1.038***	0.69	265
	(0.110)	(0.336)	(0.338)	(0.221)	(0.460)	(0.247)		
CFC	0.367***	-0.026	-1.321***	-0.467**	0.746	1.051***	0.29	1421
	(0.122)	(0.438)	(0.500)	(0.238)	(0.522)	(0.273)		
Hazardous	0.228	0.312	0.012	1.228***	1.709	2.538***	0.41	115
Waste	(0.257)	(0.252)	(0.360)	(0.389)	(1.198)	(0.639)		

*** significant at 1%, ** significant at 5%, * significant at 10%.

As can be seen from Table 2.2, ethnic fractionalization is a statistically significant explanatory variable for 6 out of the 8 pollutants studied. The point estimates also indicate that the effect of ethnic fractionalization on pollution levels has substantial practical significance as well. Looking at the estimated equation for sulfur dioxide, the point estimate of 1.038 implies that an increase in ethnic fractionalization from perfect homogeneity to perfect heterogeneity would result in a 182% increase in sulfur dioxide emissions. Likewise, the other coefficients imply an increase in carbon dioxide emissions of 92%, an increase in methane of 26%, an increase in carbon monoxide of

93%, an increase in CFCs of 186%, and an increase in hazardous waster of 1165%. The average size of the ethnic fractionalization coefficient is 0.756. This implies that for a one standard deviation increase in ethnic fractionalization country level emissions can be expected to rise by over 22% holding all else equal.

Ethnic fractionalization does not have a statistically significant effect on country level emissions of biochemical oxygen demand or nitrous oxide. The negative point estimates for the biochemical oxygen demand and nitrous oxide regressions may be evidence that ethnic fractionalization does not impair the provision of public goods such as environmental quality. However, in both cases the point estimates are very close to zero, and thus a more reasonable interpretation is that ethnic fractionalization has little or no influence on national level emissions of biochemical oxygen demand and nitrous oxide. I return to the question of ethnic fractionalization's effect on biochemical oxygen demand in the robustness analysis when I examine the determinants of local level environmental quality.

The effects of other regressors on the provision of environmental quality are inconsistent and, in a number of cases, contrary to expectation based on earlier results in the literature. For instance, La Porta et al. (2003) find that countries with French or Socialist legal origins have less public good provision than countries with English legal origin. However, the results in Table 2.2 imply that being of French legal origin significantly reduces the emissions of carbon dioxide, biochemical oxygen demand, and methane. Likewise being of Socialist legal origin significantly reduces the emissions of nitrous oxide and CFCs.

Others in the literature have suggested that geography is the main impediment to forming well-functioning institutions. A number of papers find that being near the equator is significantly correlated with poor public good provision. If geographic factors such as latitude truly inhibit public good provision, then we would expect to find a negative relationship between latitude and pollution emissions. For 1of the 8 pollutants studied, latitude does have a negative and significant effect on emissions. However, latitude has a positive and statistically significant effect on the emissions of carbon dioxide, biochemical oxygen demand, nitrous oxide, and sulfur dioxide. Indicating that for these pollutants, countries near the equator actually do a better job of providing environmental quality than countries away from the equator.

2.4 ROBUSTNESS CHECK

While the results in Table 2.2 provide strong evidence that ethnic fractionalization does inhibit the provision of environmental quality, one could argue that these results are not robust at the local level. Valuable information could be lost by aggregating data at the national level. In the statistical analysis above, it was implicitly assumed that each country's natural absorption of emitted pollutants was only a function of land size. While this may not be the case, other determinates of natural absorption are unlikely to be correlated with ethnic fractionalization. So while it is possible that other factors omitted from my regression analysis could affect the natural attenuation abilities of a country's environment, I do not believe that this omission biases the estimates of the ethnic fractionalization coefficients.

In order to ensure that the use of national aggregates is not biasing my results, I perform a robustness check by analyzing environmental quality at the local level. While it is likely that countries of equal land size have similar rates of absorption of air pollution, they may not have similar rates for water pollution. Data on national level emissions of biochemical oxygen demand may not map well into actual ambient water quality because we do not know whether those emissions are being released into one river or many rivers. Nor do we know the attenuation abilities of those rivers. For instance, larger, faster flowing rivers can accommodate much more pollution than small, slow moving rivers. In this section I control for differences in attenuation abilities, and then analyze the relationship between ethnic fractionalization and local-level ambient water quality. This enables me to make sure that the results in Section 2.3 are not biased by cross-country differences in natural attenuation abilities,

2.4.1 Data

The data I use to perform the robustness check come from Sigman (2004). Her data set has information on ambient water quality from the United Nations Nations' Global Environmental Monitoring System Water Quality Monitoring Project (GEMS/Water). Ambient water quality is measured by the mean level of biochemical oxygen demand, and pollution measurements are taken at 247 different GEMS monitoring stations around the world. Sigman's data set also has information on each river's rate of flow, upstream population, and deoxygenation rate. In addition to these variables she also has information on the political rights, trading practices and general openness of the countries in which the pollution observation have been taken. Her data also contain information on the where the pollution measurements are taken relative to international borders, to control for possible pollution spillover effects. Sigman (2002) finds evidence that international pollution spillovers impair ambient water quality, and Sigman (2004) finds that bilateral trade helps to mitigate these effects.

2.4.2 Results

In Table 2.3 below, I take the specification of Sigman (2004) and add to it the legal-origin dummy variables, latitude, and ethnic fractionalization variables used in Section 2.3. The goal of this exercise is to make sure that the results from Section 2.3 are robust to controlling for a variety of other issues omitted from the previous analysis such as the effect of international spillovers and differences in local-level environmental absorption. The equations in Table 2.2 are estimated using ordinary least squares, and the standard errors are robust to clustering at the station level.

Looking at Table 2.3, it is clear that ethnic fractionalization plays a large role in the provision of environmental quality. The point estimate of 0.997 suggest that an increase in ethnic fractionalization from perfect ethnic homogeneity to perfect ethnic heterogeneity would increase pollution levels 171%, an estimate that is significant at the five percent level. The results for other possible determinants of public good provision are mixed.

The estimated coefficient on the latitude variable once again contains the wrong sign and is not statistically different from zero at any standard level. The coefficients on the Scandinavian and Socialist legal-origin dummy variables are both statistically significant at the ten percent level, and the French legal-origin variable is statistically significant at the five percent level. As was shown in Section 2.3, however, these dummy variable are often statistically significant with negative estimated coefficients, which indicates that being of legal origin other than English actual improves environmental quality.

Table 2.3: Determinants of Local-Level Ambient Water Quality

Dependent Variable: Ambient Log(BOD)	Coef.	Std. Err
Downstream station	0.664*	0.358
Log(Trade intensity) if downstream station	-0.09*	0.0479
Upstream station	0.7003	0.484
Log(Trade intensity) if upstream station	-0.184	0.144
Border station	-0.716*	0.429
Log(Trade intensity) if border station	0.243**	0.122
Log(Upstream population)	0.056**	0.026
Own country per capita GDP	0.013	0.056
Own country per capita GDP^2	-0.0014	0.0021
Own country Log(Other openness)	0.133	0.1248
Own country Log(Political rights)	-0.485***	0.135
Log(River flow)	-0.109**	0.039
River flow missing	-0.267	0.469
River deoxygenation rate	1.397	0.883
Year	0.0213**	0.001
French legal origin	0.459**	0.169
German legal origin	0.089	0.227
Scandinavian legal origin	0.749*	0.422
Socialist legal origin	0.501*	0.275
Latitude	0.523	0.769
Ethnic fractionalization	0.997**	0.476
Constant	1.584	0.74
R – squared	0.25	
Number of observations	1387	

*** significant at 1%, ** significant at 5%, * significant at 10%.

Thus, it is difficult to interpret how legal origin affects public good provision. Overall, as evidenced by the results in Table 2.2 and Table 2.3, ethnic fractionalization is consistently and significantly correlated with higher levels of emissions and lowers levels of ambient environmental quality. The logical interpretation of these results is that ethnic fractionalization inhibits the formation of good institutions, and thus the provision of public goods such as environmental quality suffers.

2.5 CONCLUSION

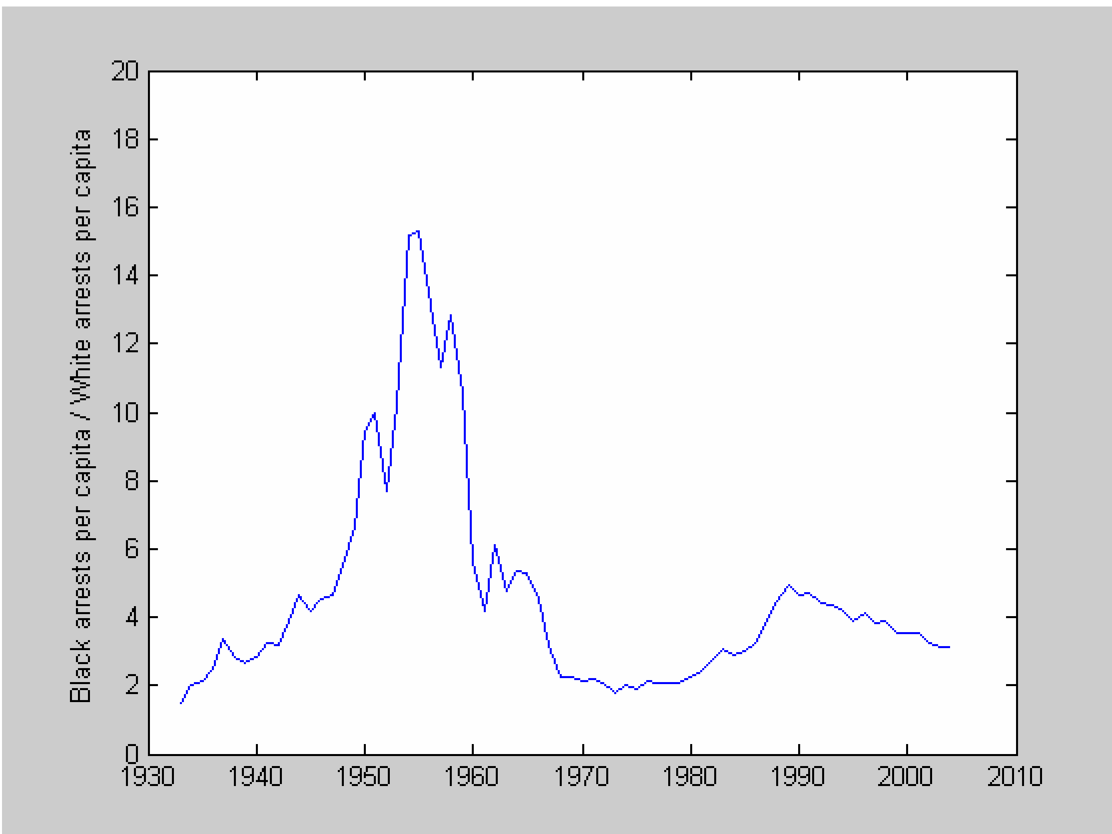
A large literature has documented the importance of quality institutions. What enables some countries and not others to develop strong, stable institutions has been a topic of hot debate. A growing literature has found evidence that ethnic fractionalization could play an important role in the development of quality institutions. This chapter adds to that literature by documenting the fact that ethnic fractionalization is significantly correlated with the poor provision of environmental quality. Ethnic fractionalization has an adverse impact on the emissions of carbon dioxide, carbon monoxide, total greenhouse gases, CFCs, methyl bromide, sulfur dioxide, methane and ambient levels biochemical oxygen demand. Other suggested determinants of public good provision such as legal origin and latitude have an inconsistent effect on environmental quality.

It is difficult to explain the consistent statistically significant relationship between ethnic fractionalization and environmental quality without coming to the conclusion that ethnic fractionalization is having an adverse impact on institutional quality. Therefore I believe that an important area of future research is to understand more about the ways in which ethnic fractionalization effects institutional development. The results of this chapter and others make a strong case that ethnic strife is a likely culprit in poor institutional outcomes.

Chapter 3: Divergence Followed By Convergence: The Propagation of Arrest Rates in Victimless Crimes

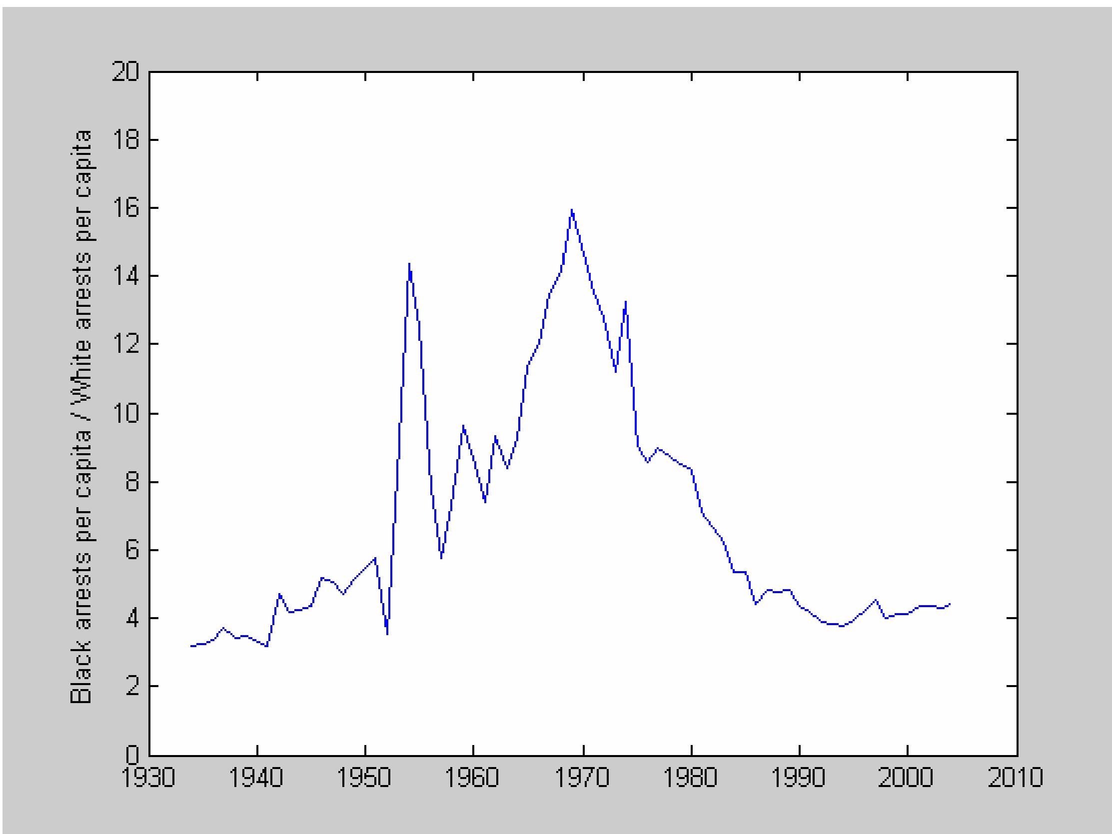
Using national data from the FBI's Uniform Crime Statistics and the US Census, a comparison of the per capita arrest rates for victimless crimes show not only that these rates differ across racial lines, but that the ratios of black to white per capita arrests, "B-W ratio," follow a distinct, hump-shaped time series.

Figure 3.1: B-W Ratio for Drug Arrests



For drug and prostitution arrests, this series is displayed in Figures 3.1 and 3.2. The hump-shaped pattern in the B-W ratio for drug offenses in Figure 3.1 peaks first in 1955, and then again in the post Vietnam era. An identical hump-shaped pattern in the B-W ratio for prostitution offenses is also seen in Figure 3.2, but peaking in 1969. These figures show three distinct hump-shaped patterns in the B-W ratio for drug and prostitution offenses and are unlikely to be the result of random fluctuations.

Figure 3.2: B-W Ratio for Prostitution Arrests



In general, the number of drug and prostitution arrests per capita is rising over time. This fact is consistent with, and likely caused by, rising law enforcement expenditures. However, the pronounced humped shaped pattern in the B-W ratio for both the drug and prostitution offenses is difficult to explain. The peak in the B-W ratio for drug offenses occurs 14 years before the peak in the B-W ratio for prostitution offenses and 10 years before the number drug arrests per capita start rapidly rising with the war on drugs. Likewise, the peak in the B-W ratio for prostitution offenses does not correspond to any large changes in total prostitution arrests per capita. In 1969, the cumulative growth rate in prostitution arrests per capita was 9.1%, very close to the average growth rate for the 1960s of 6.1%. Thus it is hard to argue that the hump-shaped pattern in the B-W ratio is somehow related to an exogenous shock to law enforcement expenditures or focus.

The hump-shaped pattern in the two B-W ratios rises and falls in a very steady and persistent pattern. Thus it is difficult to understand the peaks in the B-W ratios as random shocks to number of black American arrested relative to white American. The time series of both the prostitution and drug B-W ratios are extremely persistent. Using an augmented Dickey Fuller test we cannot reject the presence of a unit root at any standard level of significance. However, both time series clearly look to be returning to their initial values. The obvious hump-shaped pattern in the arrest ratios combined with their strong statistical persistence make a compelling case against the argument that random shocks to the black arrest rate could account of the peak in the B-W ratios.

One such underlying process that could explain the hump-shaped pattern in the B-W ratios is increasing and then decreasing levels of racism among law enforcement.

However, two facts are strictly at odds with this conjecture. First, as noted before, the peak in the B-W ratio for drug offenses occurs 14 years prior to the peak in the B-W ratio for prostitution offenses. It is highly unlikely that racism among drug enforcement officers rose and then fell 14 years before such an increase and then decrease occurred for prostitution enforcement officers.

This chapter addresses the question of whether it is possible that a peak in the B-W ratio is the result of rational law enforcement behavior in a world in which the underlying rate of criminal behavior is equal across race and stationary in time. We present a model to explain Figures 3.1 and 3.2 and then discuss the parameters and variables that are necessary for the emergence of the hump-shaped pattern. The underlying forces driving the model and the relevant policy implications are discussed as well.

The rest of the chapter is organized as follows. Section 3.1 discusses the data. Section 3.2 presents our model and compares it to the data. Section 3.3 estimates our model for the static case and Section 3.4 concludes.

3.1 DATA

The time series of the white population in the United States between 1933 and 2004 is derived using a combination of data collection and interpolation. From 1933-1979, the total white population is taken from the US Bureau of the Census. In the years where estimates are only available by age, all ages were summed. From 1980-1999 the

US Bureau of the Census only has records of the total white population for 1980, 1990 and 2000. We interpolate the population estimates between these years using the formula

$$pop_{i,\tau+t} = pop_{i,\tau}(pop_{i,\tau+10} / pop_{i,\tau})^{t/10}, \tag{3.1}$$

where $i = w, b$, $\tau = \{1980, 1990\}$, and $t = \{n\}_{n=1}^{n=10}$. For 2000-2004, we return to the recorded total white population recorded by the US Bureau of the Census.

Since the total black population of the United States is not a category recorded by the US Bureau of the Census prior to 1960, the methodology for determining the black population is slightly different than for the white population. From 1933-1959 we use the total non-white population as recorded by the US Bureau of the Census. Then from 1960-1979 we use the total black population recorded by the US Bureau of the Census. From 1980-1999, the US Bureau of the Census only has records of the total black population for 1980, 1990 and 2000. We interpolate the population estimates between these years using equation (3.1). For 2000-2004, we again use the recorded total black population recorded by the US Bureau of the Census.

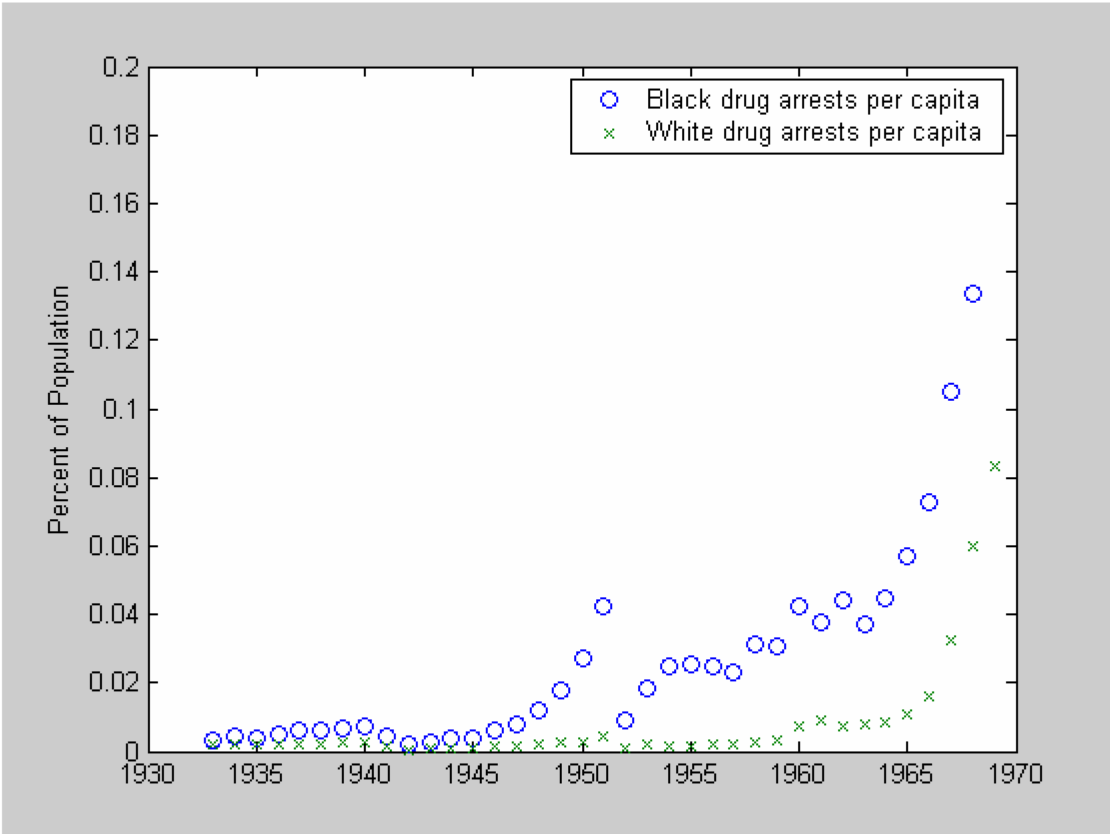
Arrest rates from 1933-2004 are recorded by the FBI in the Uniform Crime Statistics. We record data for the total number of drug arrests by race, recorded as Drug Abuse Violations, and prostitution arrests by race, listed as Prostitution and Commercialized Vice. From 1952-1959, data is only recorded in cities with total population of over 2,500. In 1960-1961, city and rural data are given separately and we use the sum. In 1962, only city data are given. Since less than five percent of arrests are attributed to rural areas in 1960 and 1961, we do not modify the "city-only" data from the Uniform Crime Reports for the years that full data are not available. In 1933 the closest category to prostitution is "sex offenses (excluding rape)." To avoid a potential discrepancy resulting from this, we make 1934 the first year of our prostitution data series.

For drug and prostitution offenses, we divide the number of white arrests by the total white population and the number of black arrests by the total black population to obtain four time series of arrest rates. Further, we obtain the B-W ratio for drug and prostitution offenses by dividing the black arrest rate by the white arrest rate for each offense.

Viewing the B-W ratio for drug offenses, it is seen that in 1933 the ratio began at 1.49 before increasing to a peak of 15.26 in 1955. After 1955 the B-W ratio for drug offense declines rapidly and levels off in the mid 1970s at value slightly over 2. However, starting in the late1970s the humped shaped pattern in the B-W ratio for drug offenses repeats itself, though in this case reaching a peak of only 4.96 in 1989. Post 1989 the B-W ratio for drug offenses then gradually declines to just over 3 in the year 2004.

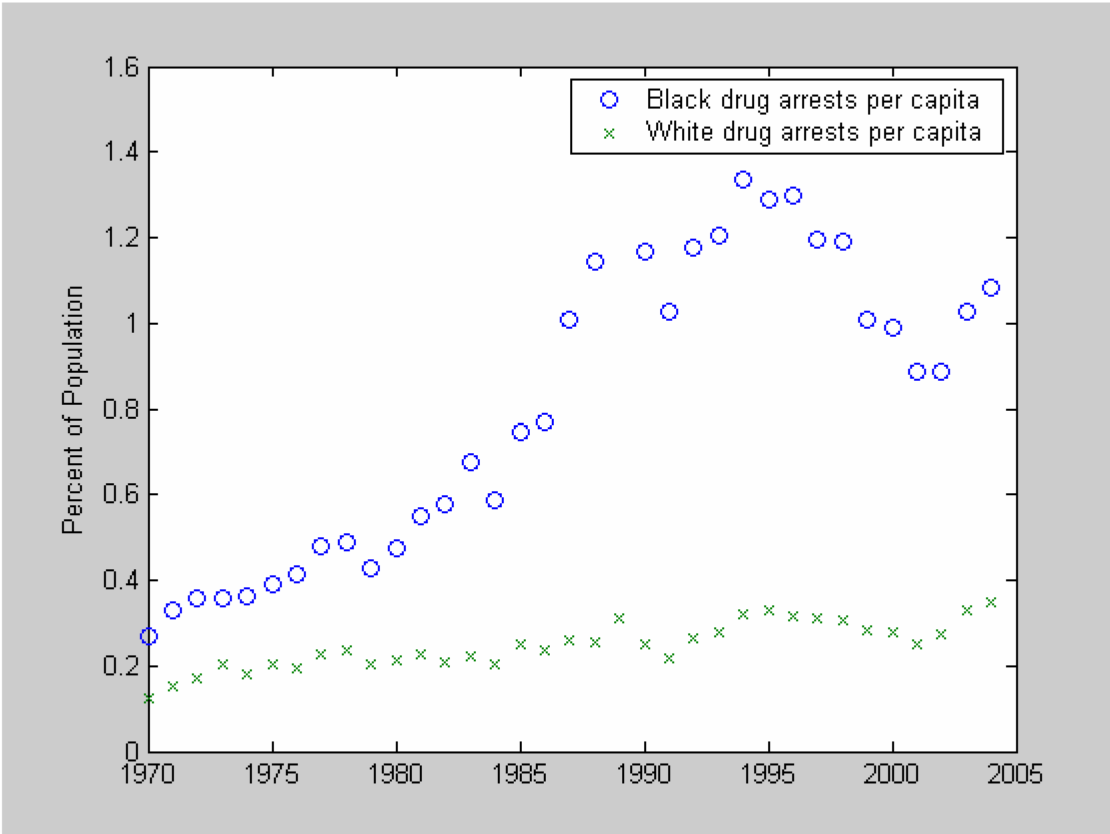
The total number of drug arrests over the period 1933-2004 also displays some interesting features. Total arrests per capita rise over the entire sample 1933-2004 with an average annual cumulative growth rate of 7.56%. However, the growth in arrests per capita is far from constant. Over the period 1933-1964 the mean growth rate is 5.6% and over the period 1976-2004 the mean growth rate is 2.4%. While in the intermediate period 1965-1975 the mean growth rate is 26.4% and corresponds to the beginning of the war on drugs.

Figure 3.3: Per Capita Drug Arrests 1933-1969



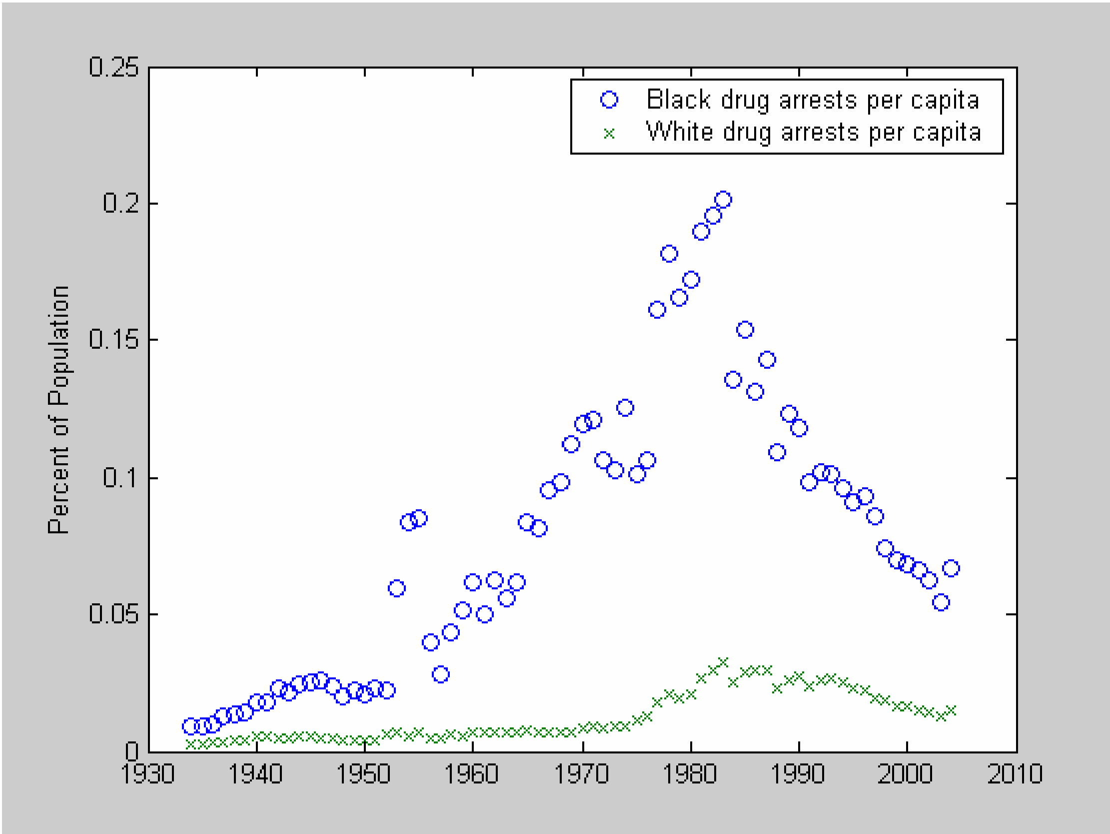
The B-W ratio for prostitution offenses contains the same hump-shaped pattern as the B-W ratio for drug offenses. The B-W ratio for prostitution offenses begins in 1934 at a value of 3.2 and increases to a maximum value of 15.94 in 1969. The B-W ratio for prostitution offenses then declines to a value of 4.4 in 2004. Total prostitution arrests per capita steadily increase until 1983 and then decline over the rest of the sample. In 1983, 0.054% of the population was arrested for prostitution whereas in 2004 and 1934 the percent of the population arrested was 0.022% and 0.004% respectively.

Figure 3.4: Per Capita Drug Arrests 1970-2004



For all peaks in the B-W ratio, the fall is precipitated by an increase in the white arrest rate, and it is only after the ratio has begun to fall that we see a reduction in the black arrest rate. In other words, law enforcement officers are still arresting an increasing percentage of the black population for a number of years after the peak in the B-W ratios and further evidence that rising and then falling racism towards black Americans cannot explain the hump-shaped pattern seen in the data. This phenomenon can be clearly seen in Figures 3.3, 3.4, and 3.5 below.

Figure 3.5: Per Capita Prostitution Arrests 1934-2004



3.2 THE MODEL

Based upon the findings of the previous literature, our model has six assumptions. First, communities are separated by race. Manning (2004) cites police as classifying drugs as "black" or "white" drugs according to the racial group that primarily uses them. Additionally, he documents that black officers are primarily used to obtain black informants, while white offers are used to obtain white informants. Second, the arrest rate in a community is an increasing function of informants per capita and law enforcement budget per capita in that community. William et al (1979) details the role of informants in generating arrests. They also make note of binding budget constraints as being the primary limitation in arrest rates. Third, the objective of law enforcement is to maximize the present discounted number of total arrests. Kansas City Police Chief Joseph McNamara (2001) states that promotions are based on making "good arrests" and that on a yearly basis "cops are pressured to fulfill a drug arrest quota." From William et al (1979) we know that there is no written objective for law enforcement units in reference to drug enforcement. We therefore use this extension of the suggestions set forth in Shoup (1964) about police maximization.

Fourth, arrest rates do not vary sufficiently to affect criminal behavior. In contradiction to the assumptions of Becker (1968), Levitt (2002) showed that in a closed, artificial environment that when the increase in the probability of detection is sufficiently small, there is no change in law-violating behavior. Testing this result for drug offenders, we find the correlation between the change in the arrest rate and the change in drug usage is not statistically different from zero.[7] Fifth, informants in period $t + 1$ are a fixed percentage of arrestees in period t. William et al (1979) finds that informants are compiled from those arrests on lesser charges. Since data does not exist on the number and race of informants over the time range we examine, we are forced to infer the number of informants based upon prior arrests. A fixed fraction was chosen as it provides the most rigorous conditions for matching the data. Sixth, total law enforcement spending is exogenously determined. Law enforcement budgets are determined by local and federal

[7] Data obtained from Monitoring the Future surveys over the period 1975-2004. Result is robust to use of data from National Household Survey on Drug Abuse.

legislatures. Such expenditures cannot be modified at the law enforcement level and are typically set many years in advance.

The probability of arrest for each race is a joint distribution cumulative density in informants per capita and money per capita. The total arrests in period t is thus

$$(3.2) \quad A^i = p^i c^i (1 - e^{-\gamma A^i_{-1}/p^i})(1 - e^{-\mu m^i/p^i})$$

where m^i is the fraction of money allocated toward enforcement in community i for $i = w,b$, μ_t is the effective law enforcement budget, γ_t is the effective percentage of arrestees converted to informants the following period, and p^i_t is the population in the community of race i.

The law enforcement optimization problem can be reduced to

$$(3.3) \quad V(A^w_{-1}, A^b_{-1}, p^w, p^b, \mu) = \max_{m^w} \sum_{i=w,b} A^i(A^i_{-1}, p^i, \gamma, \mu, m^i) + \beta V(A^w, A^b, p^{w'}, p^{b'}, \mu')$$

To ensure that a solution to (3.3) exists, it is necessary that $p^b_t, p^w_t,$ and μ_t grow at the identical rates. As a result, per capita effective law enforcement budget is constant, and it is possible to simplify (3.3) to the stationary problem:

$$(3.4) \quad V(a^w_{-1}, a^b_{-1}) = \max_{m^w, m^b} \sum_{i=w,b} \frac{p^i}{\sum_{j=w,b} p^j} c^i (1 - e^{-\gamma a^i_{-1}})(1 - e^{\mu^i m^i}) + \beta V(a^w, a^b),$$

where for $i = w,b$, $a^i = A^i / p^i$, and β has been defined to take into account both time discounting and population growth. We assume constant values for the racial composition of the population, $p^i / \sum_{j=w,b} p^j$, the effectiveness of informants, γ, the effective law enforcement budget supply per black citizen, μ^b, and the effective law enforcement budget per white citizen, μ^w.

The per capita arrest rate for sector $i = w,b$ is

(3.5) $$a^i = c^i (1 - e^{-\gamma a_{-1}^i})(1 - e^{-\mu^i m^i}) .$$

Having bounded the effective law enforcement budget and population ratio, we are able to solve equation (3.4) by value function iteration over the range $a^i \in [0,1]$, $i = w,b$, and the maximization is taken with respect to $m^i \in [0,1]$.

We are then capable of observing the sequence of per capita arrest rates by race as well as the series of B-W ratios, $\{a_i^b / a_i^w\}_{t=t_0}^{t=t_{\max}}$, that originate from an initial B-W ratio. Since population growth is removed to make the problem stationary, it is necessary to redefine $\beta = \beta_d \eta$ where β_d is the rate at which law enforcement discounts future time and η is the population growth rate.

Due to the nature of the problem we are addressing, we focus only on arrest paths originating with per capita arrest rates below the steady state value for both sectors, $a_{-1}^i < c^i (1 - e^{-\gamma a_{-1}^i})(1 - e^{-\mu (p^i c^i / \sum_{i=w,b} p^i c^i)})$.[8] Without loss of generality, we consider only the case where the initial B-W ratio is above the underlying ratio of criminal behavior, $\frac{a_{-1}^b}{a_{-1}^w} > \frac{c^b}{c^w}$.

The B-W ratio may follow three possible paths over time: divergence, convergence, or divergence followed by convergence (DFC). In the divergence case,

$\lim_{t\to\infty} \frac{a^b}{a^w} \to \infty$ and the entire law enforcement budget is eventually used in the black community. In the convergence case, $(\frac{a^b_{-1}}{a^w_{-1}}) > (\frac{a^b}{a^w}) \geq (\frac{c^b}{c^w})$ and $\lim_{t\to\infty} m^i = p^i c^i / \sum_{i=w,b} p^i c^i$. Hence, the ratio immediately moves toward the underlying ratio of criminal behavior. In the DFC case, originally, $(\frac{a^b}{a^w}) > (\frac{a^b_{-1}}{a^w_{-1}}) > (\frac{c^b}{c^w})$, until a peak B-W ratio is reached at that point, the ratio begins to converge to the underlying ratio.

The fraction of the budget allocated toward the white community is approximately

(3.6) $$m^w = \tfrac{1}{2} + \tfrac{1}{2\mu}[\ln(\tfrac{p^w c^w}{p^b c^b}) + e^{-\gamma a^b_{-1}} - e^{-\gamma a^w_{-1}} + \beta\gamma(a^w c^w (1 - e^{-\mu^w m^{w'}}) - a^b c^b (1 - e^{-\mu^b m^{b'}}))].$$

As discussed in the previous section, the distinction between convergence and divergence is that for convergence, $\lim_{t\to\infty} m^i = p^i c^i / \sum_{i=w,b} p^i c^i$. Smaller values of μ, γ, and β increase the likelihood of divergence in $(\frac{a^b}{a^w})$ from $(\frac{c^b}{c^w})$. Conditional on divergence, DFC will not occur if $(\frac{a^w}{a^w_{-1}}) < 1$, since $\partial a^i / \partial a^i_{-1} > 0$.

Figure 3.6 plots the B-W ratio, white arrest rate, black arrest rate, and total arrest rate, for a set of initial conditions and exogenous variables that result in DFC. As explained above, variations in β effect the range of μ and γ for which DFC will occur. Additionally, for a given μ and γ, it can be seen that the timing of the peak is decreasing in β. For lower initial B-W ratios, a lower β is necessary to achieve DFC.

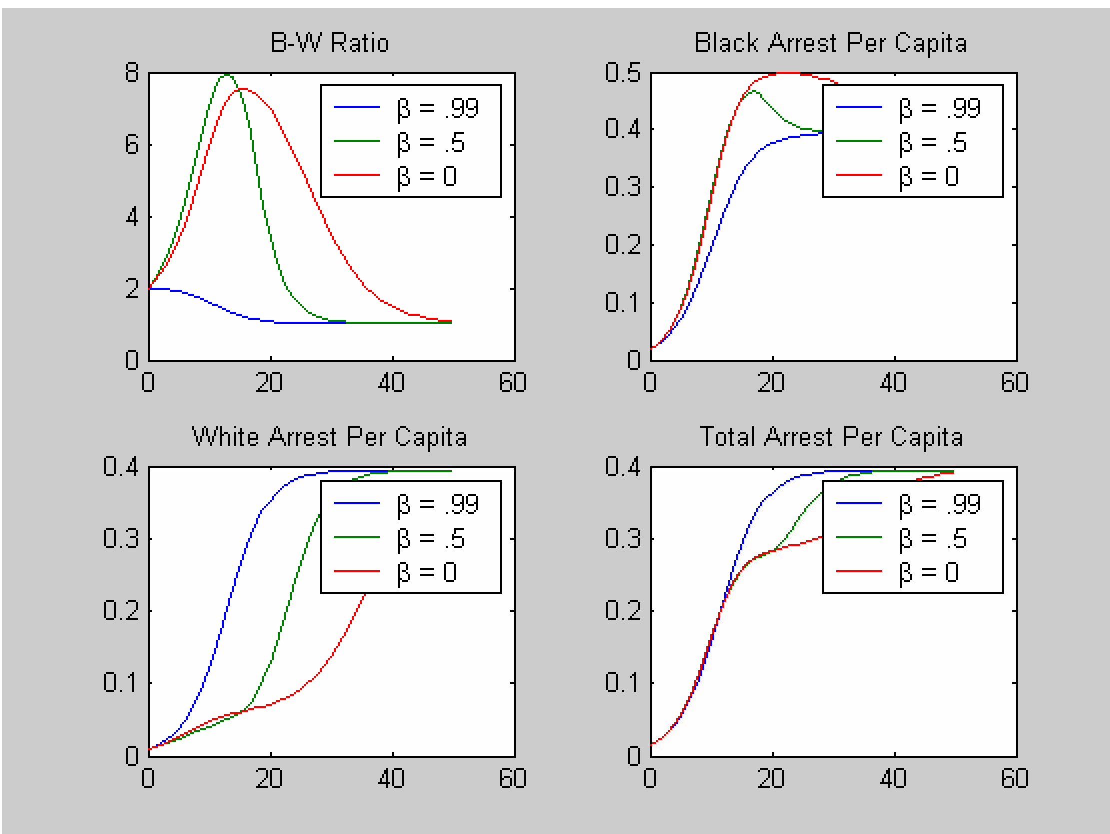
---

[8] In the case of higher per capita arrest rates, the results are similar, but the peak represents movement toward converge followed by ultimate divergence.

However, when the initial B-W ratio is high, low β's result in divergence and higher β's result in DFC.

In all such paths, the movement of the B-W ratio down from the peak is always precipitated by an increase in the white arrest rate and is followed by a decrease in the black arrest rate. Thus the DFC generated by our model replicates many of the key features of the B-W ratios for prostitution and drug offenses observed in the data.

Figure 3.6: DFC Paths for Varying β's



We see in Figure 3.6 that β must be sufficiently small to achieve DFC. Since DFC is present when there is no forward looking component to police maximization functions, $\beta = 0$, it must be that the elements of the model that cause the hump-shaped pattern lie entirely within the static maximization problem and the evolution of informants. Additionally, this is the simplest case to solve analytically and empirically while providing the best insight into the inner workings of the model. For these reasons, we examine the $\beta = 0$ case in more detail.

3.3 STATIC PROBLEM

In the case that $\beta = 0$, the value function of the previous section can be reduced to a one period maximization problem

$$(3.7)\quad \begin{aligned} &\max_{m_t^b, m_t^w} A_t = p_t^w c_t^w \left(1 - e^{-\gamma \frac{A_{t-1}^w}{p_t^w}}\right)\left(1 - e^{-\frac{\mu_t m_t^w}{p_t^w}}\right) + p_t^b c_t^b \left(1 - e^{-\gamma \frac{A_{t-1}^b}{p_t^b}}\right)\left(1 - e^{-\frac{\mu_t m_t^b}{p_t^b}}\right) \\ &m_t^b + m_t^w = 1 \end{aligned}$$

Unlike the value function of Section 3.2, equation (3.7) has a closed form solution.

$$(3.8)\quad m_t^w = \begin{cases} 0 & \dfrac{p_t^w p_t^b \ln(\alpha)}{\mu_t \left(p_t^w + p_t^b\right)} + \dfrac{p_t^w}{p_t^w + p_t^b} < 0 \\ 1 & \dfrac{p_t^w p_t^b \ln(\alpha)}{\mu_t \left(p_t^w + p_t^b\right)} + \dfrac{p_t^w}{p_t^w + p_t^b} > 1 \\ \dfrac{p_t^w p_t^b \ln(\alpha)}{\mu_t \left(p_t^w + p_t^b\right)} + \dfrac{p_t^w}{p_t^w + p_t^b} & else \end{cases}$$

where

$$(3.9)\quad \alpha_t = \frac{c_w\left(1 - e^{-\gamma A_{t-1}^w}\right)}{c_b\left(1 - e^{-\gamma A_{t-1}^b}\right)}.$$

Calibration of the model's parameters is carried out as follows: (i) guess an initial γ and $\{\mu_t\}_{t=0}^{\tau}$, (ii) using (3.8), (3.2), and $\{A_{-1}^w, A_{-1}^b, p_0^w, p_0^b\}$, determine $\{A_0^w, A_0^b\}$, and (iii) using the sequences $\{p_t^w\}_{t=0}^{\tau}$ and $\{p_t^b\}_{t=0}^{\tau}$ in conjunction with $\{A_t^w, A_t^b\}_{t=-1}^{\tau-1}$ from (ii) generate and update the sequence $\{A_t^w, A_t^b\}_{t=0}^{\tau}$ as t grows. We set μ_t to grow at 1.11% each year, the average US population growth rate from 1934-2004, to maintain a constant per capita law enforcement budget. Therefore only μ_0 is free to be chosen. No growth in γ is necessary as the arrest rate rises in conjunction with the population.

We search over positive values of γ and μ_0 using the Nelder-Mead method to minimize the sum of squared residuals between our model's simulated B-W ratio and the B-W ratio in the data. Thus γ and μ_0 are estimated only using data on the B-W ratio.

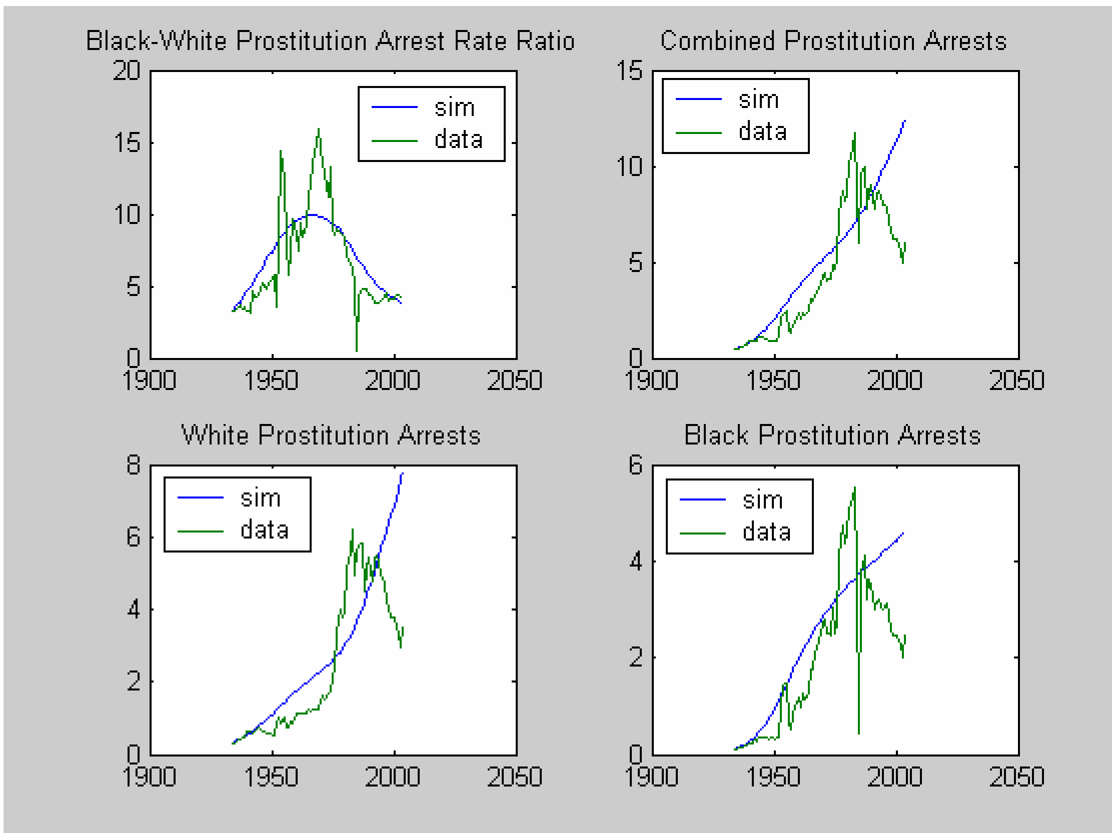
For prostitution offenses from 1934-2004, we set the underlying crime commission rate, c^w and c^b, equal to .005 for the entire period.[9] Figure 3.7 below compares the actual data with our simulation for the B-W ratio, the total number of prostitution arrests, the number of white Americans arrested for prostitution, and the number of black Americans arrested for prostitution. Since only the distance from the B-W ratio was conditioned over during our maximization, the total arrest rates provide a rough confirmation of our model's accuracy.

The simulation does a nice job of capturing the overall hump-shape seen in the data, though the data has a much more pronounced peak. It also captures the strong

[9] These estimates come from the 1992 National Health and Social Life Survey that estimates the percentage of the population involved with prostitution at 0.5%.

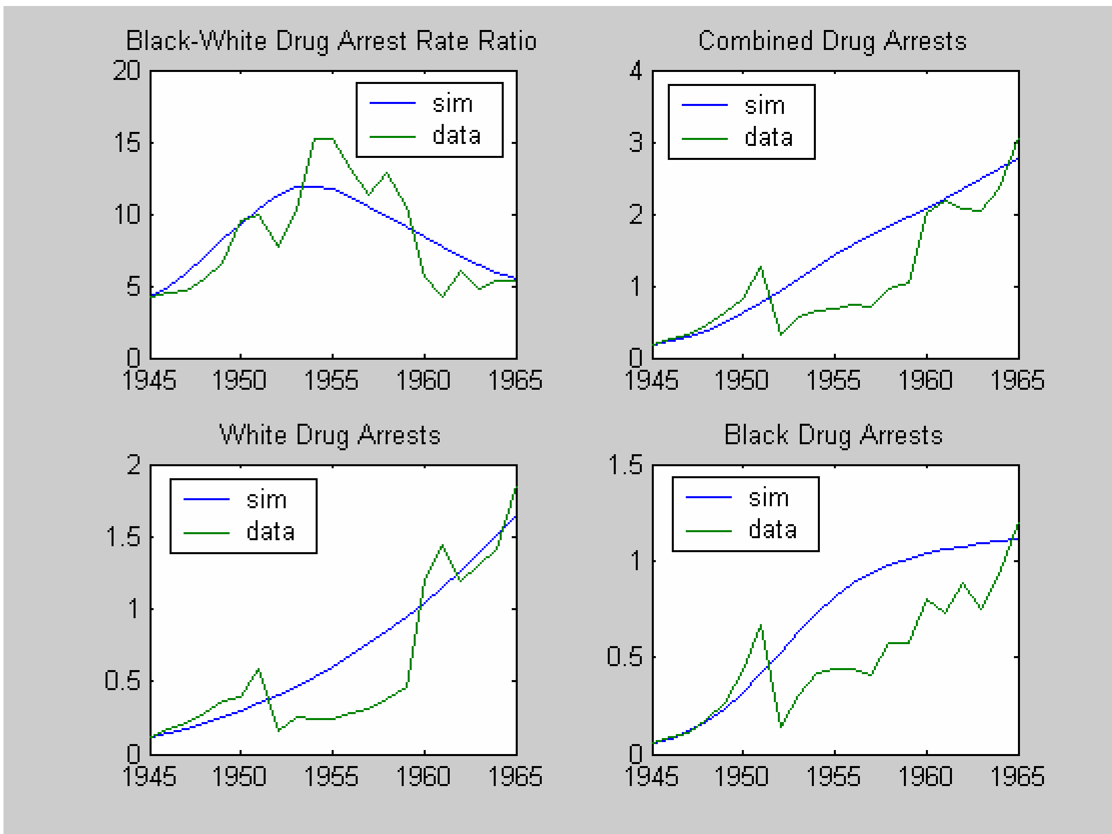
exponential trend in prostitution arrests from through the early 1980s, but fails to match the decline of total arrests during the latter part of the sample. These discrepancies can be corrected if we were to increase the underlying crime commission rate and then allow it to fall over time.

Figure 3.7: Prostitution Arrests 1934-2004



Next simulate the model for a period of very low crime commission rates using data on the B-W ratio for drug offenses from 1945-1965. We exclude observations before 1945 since World War II creates a dramatic break in the drug arrest data. For similar reasons we choose to end the sample in the 1965 before drug use rates skyrocket in the late 1960s. We set the drug use rate, c^w and c^b, equal to 0.01 for the 1945-1965.[10] Figure 3.8 graphs these results.

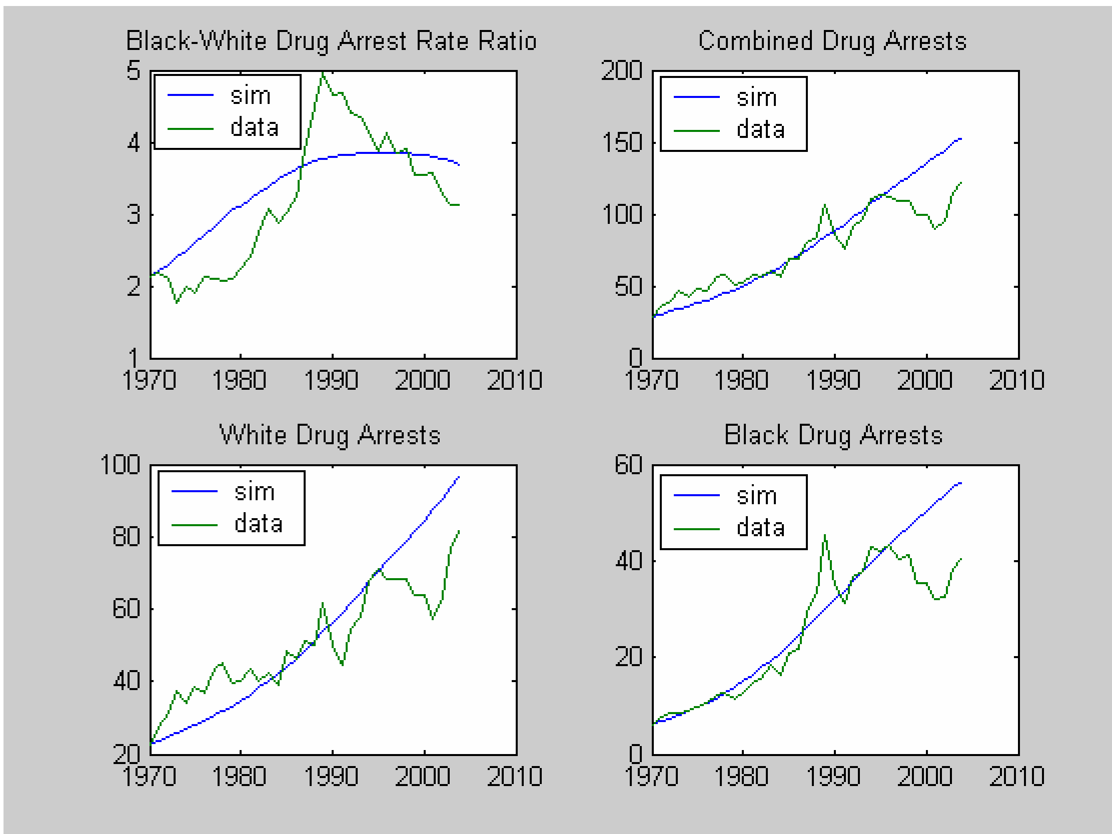
Figure 3.8: Drug Arrests 1945-1965



[10]. This estimate of the drug use rate was chosen as a multiple of the number of drug addicts estimated by the Federal Bureau of Narcotics in 1954.

Our final simulation is for drug offenses from 1970-2004. For this sample, we set c^w and c^b, equal to 0.08, an estimate derived from the National Household Survey on Drug Abuse.

Figure 3.9: Drug Arrests 1970-2004



The same four graphs are displayed in Figure 3.9 as were displayed in the previous figures and each graph has a plot of the simulation from our model and the data from the FBI Uniform Crime statistics. Similar to the graphs from Figures 3.7 and 3.8 the model's simulation of the B-W ratio for drug offenses is smooth compared to the data but captures the trend in the B-W ratio and actual arrests. Lowering the calibrated drug abuse rate results in a better fit of arrests, but reduces the fit of the B-W ratio. Similarly, adding further complexities, including variations to the rate of drug use during the sample or random shocks, would enable the model to better match the data and level off in total arrests at the end of the sample. We do not document these variations as the goal of this chapter is to explain the underlying dynamics of these arrest rates and is not concerned with estimating more parameters to match year to year arrest rate volatility.

3.4 CONCLUSION

It has previously been believed that elements of racism reside in law enforcement today. Examining this in the area where racism should be most prevalent, victimless crimes, we uncover three similar time series of arrest rates that appear to depict the existence of racism in law enforcement. However, through analysis, we provide an alternate explanation for such patterns: lack of forward-looking behavior by law enforcement.

This chapter shows that it is possible that given for the proper conditions, it is possible for the results of prior racism, a greater number of informants amassed in a minority community, to resonate through time if law enforcement agents are concerned with maximizing arrests in the current period as opposed to considering the future.

We have not explored other possible explanations for these DFC paths, which may exist. Instead, we have shown that it is possible to generate such paths for the case of stationary criminal behavior and by rational, non-biased decision making on the part of law enforcement.

Given our findings, this chapter could be taken as making the following policy recommendation: Law enforcement agents need to be given sufficient incentives to be more forward looking in their behavior in a effort to flush out the remnants of prior racism that are still effecting arrest rates today.

Appendix

A.1 Estimated Variance-Covariance Matrix of Model Parameters

	c_1	σ_j	W	ψ	γ_0	γ_1
c_1	3177.2	-0.65969	-8838.9	-0.033347	0.000114	-1.87E-07
σ_j	-0.65969	0.000465	2.1903	1.07E-06	2.18E-08	-3.21E-12
W	-8838.9	2.1903	26530	0.053539	-0.00012	3.66E-07
ψ	-0.033347	1.07E-06	0.053539	1.19E-06	-5.44E-09	5.36E-12
γ_0	0.000114	2.18E-08	-0.00012	-5.44E-09	3.01E-11	-3.07E-14
γ_1	-1.87E-07	-3.21E-12	3.66E-07	5.36E-12	-3.07E-14	3.54E-17

A.2 Hubbert Model (1956)

The Hubbert model assumes that cumulative oil production follows a logistic growth path.

$$\text{(A.1)} \quad CX_t = \frac{TRR}{1+\exp(-\delta(t-t_0))}$$

In equation (A.1) CX_t is cumulative aggregate oil production in year t, TRR is total recoverable reserves, t_0 is the year of peak oil production, and δ is a parameter that determines the steepness of the logistic growth path. Differentiating equation (A.1) with respect to time yields:

$$\text{(A.2)} \quad X_t = \frac{TRR\,\delta\exp(-\delta(t-t_0))}{(1+\exp(-\delta(t-t_0)))^2},$$

where X_t is aggregate oil production in year t. Solving equation (A.1) for $-\delta(t-t_0)$ and substituting into equation (A.2) yields:

(A.3) $$X_t = \delta CX_t - \frac{\delta}{TRR} CX_t^2 .$$

In practice, estimates of δ and TRR can be obtained by regressing current oil production on cumulative oil production and cumulative oil production squared. The estimates of δ and TRR can then be used to forecast future oil production.

References

Adelman, M. A., 1993, *The Economics of Petroleum Supply*, Cambridge: The MIT Press.

Alesina, A, Baqir, R., and Easterly, W., "Public Goods and Ethnic Divisions," *Quarterly Journal of Economics*, 1999, 114(4), 1243-1384.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R., "Fractionalization," *Journal of Economic Growth*, 2003, 8, 155-194.

Becker, G.S., "Crime and Punishment: an Economic Approach," *Journal of Political Economy*, 1968, vol. 76, no 2, 169-217.

Becker, G. S, and Landes, W., 1974, *Essays on the Economics of Crime and Punishment*, New York: NBER.

Biderman, A.D. and Lynch, J.P., 1991, *Understanding Crime Incidence Statistics: Why the UCR Diverges from the NCS*, New York: Springer-Verlag.

Brajer, V. and Hall, J., "Changes in the distribution of air pollution exposure in the Los Angeles Basin from 1990 to 1999," *Contemporary Economics Policy*, 2005, vol. 23, no. 1, 50-58.

Brooks, N. and Sethi, R., "The Distribution of Pollution: Community Characteristics and Exposure to Air Toxics," *Journal of Environmental Economics and Management*, 1997, 32, 233-250.

Cairns, R.D. and Van Quyen, N., "Optimal exploration for and exploitation of heterogeneous mineral deposits," *Journal of Environmental Economics and Management*, 1998, 35, 164-189.

Campbell, C., 1997, *The Coming Oil Crisis*, Multi-Science Publishing.

Campbell, C. and Laherrere, J., 1998, "The End of Cheap Oil," *Scientific American*, 278, 78-84.

Carr-Hill, R. A. and Stern, N. H., "An Econometric Model of the Supply and Control of Recorded Offenses in England and Wales", *Journal of Public Economics*, 1973, vol. 2, no. 4, 289-318.

Carr-Hill, R. A. and Stern, N. H., 1977, "Theory and Estimation in Models of Crime and its Social Control and their Relations to Concepts of Social Output," in M.S. Feldstein and R.P. Inman (eds), *The Economics of Public Services*, London: Macmillan, 116-47.

Carr-Hill, R. A. and Stern, N. H., 1979, *Crime, the Police and Criminal Statistics*, London: Academic Press.

Cremer, J. and Salehi-Isfahani, D., 1991, *Models of the World Oil Market*. New York: Harwood Academic Publishers.

Deffeyes, K., 2005, *Beyond Oil: The View from Hubbert's Peak*, Hill and Wang.

Deffeyes, K., 2002, *Hubbert's Peak: The Impending World Oil Shortage*, Princeton University Press.

Ehrlich, I., "Participation in Illegitimate Activities: a Theoretical and Empirical Investigation", *Journal of Political Economy*, 1973, vol. 81, no. 3, 521-64.

Energy Information Administration, 2004, *Long Term Oil Supply Scenarios*, Washington, D.C.

Energy Information Administration, 2006, *Oil and Gas Lease Equipment and Operating Costs 1987 Through 2005*, Washington, D.C.

Energy Modeling Forum, 1982, "World Oil: Summary Report, EMF6," Stanford University.

Energy Modeling Forum, 1991, "International Oil Supplies and Demands: Summary Report, EMF11," Stanford University.

Gately**,** D., "OPEC's Incentives for Faster Output Growth," *Energy Journal*, 2004, 25, 75-96.

Gately, D., "A Ten-Year Retrospective: OPEC and the World Oil Market," *Journal of Economic Literature*, 1984, 22, 1100-1114.

Green, W., 2003, *Econometric Analysis*, 5th Ed., Prentice Hall.

Havlena, D. and Odeh, A. S., "The Material Balance as an Equation of a Straight Line," *Journal of Petroleum Technology*, 1963, 228, 869-900.

Havlena, D. and Odeh, A. S., "The Material Balance as an Equation of a Straight Line. Part II – Field Cases," *Journal of Petroleum Technology*, 1964, 231, 815 – 822.

Hoetelling, H., "The Economics of Exhaustible Resources," *Journal of Public Economics*, 1931, 39, 137-175.

Hoover, J. E., 1965, *Crime in the United States. The Uniform Crime Report-1963*, Federal Bureau of Investigation., Boston: Beacon Press.

Hubbert, M. K., 1956, "Nuclear Energy and the Fossil Fuels," *American Petroleum Institute's Drilling and Production Practice*, 7-25.

Johnston, L. D., O'Malley, P. M., Bachman, J. G., & Schulenberg, J. E., 2006, *Monitoring the Future national survey results on drug use, 1975-2005. Volume I: Secondary school students*, NIH Publication No. 06-5883, Bethesda, MD: National Institute on Drug Abuse, 684.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R., "The Quality of Government," *Journal of Law, Economics and Organization*, 1999, 15(1), 222-279.

Laumann, E. O., Gagnon, J. H., Michael, R. T., and Michaels, S., 1994, *The Social organization of sexuality in the United States.* Chicago: University of Chicago Press.

Lee, B. and Ingram, B. F., "Simulation Estimation of Time Series Models," *Journal of Econometrics*, 1989, 47, 197-205.

Levitt, S., "Testing the Economic Model of Crime: The National Hockey League's Two-Referee Experiment," *Contributions to Economic Analysis and Policy*, 2002, vol. 1, no 1, article 2.

Litzenberger, R. H. and Rabinowitz, N., "Backwardation in Oil Futures Markets: Theory and Empirical Evidence," *The Journal of Finance*, 1995,50, 1517-1545.

Lucas, R. "Expectations and the Neutrality of Money," *Journal of Economic Theory*, 1972, 4, 103-24.

Manning, P. K.,2004, *The Narcs' Game: Organizational and Informational Limits on Drug Law Enforcement*, 2nd edition, Prospect Heights, IL: Waveland Press Inc.

Mason, C.F., "Non-Renewable Resources with Switching Costs," *Journal of Environmental Economics and Management*, 2001, 65-81.

Michael, R. T., Gagnon, J., H., Laumann, E. O.,and Kolata, G., *Sex in America: A definitive survey*, 1995, Boston: Little, Brown.

Musto, D. F., 1999, "The American Disease: Origins of Narcotic Control." 3rd Edition. New York: Oxford University Press.

Nelder, J.A. and Mead, R., "A Simplex Method for Function Minimization," *Computer Journal*, 1965, 7, 308-313.

Newey, W. K. and West, K. D., 1987, "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703-708.

Phillips, L. and Votey, H. L., "An Economic Analysis of the Deterrent Effect of Law Enforcement on Criminal Activity," *Journal of Criminal Law, Criminology and Police Sciences*, 1972, vol. 63, no. 3, 330-42.

Pindyck, R. S., "Optimal Production of an Exhaustible Resource When Price is Exogenous and Stochastic," *Scandinavian Journal of Economics*, 1978, 277-288.

Pindyck, R. S., "Uncertainty and Exhaustible Resource Markets," *The Journal of Political Economy*, 1980, 88, 1203-1225.

Pindyck, R. S., "The Optimal Exploration and Production of Nonrenewable Resources," *The Journal of Political Economy*, 1978, 86, 841-861.

Pozo, Susan. (1996) "Price Behavior in Illegal Markets", (Aldershot, England: Avebury).

Pyle, David J. "The economics of crime and law enforcement." St. Martin's Press. New York: 1983.

Pyle, David and MacDonald, Ziggy, ed. "Illicity Activity: The economics of crime, drugs and tax fraud." Ashgate Publishing Company, Aldershot: 2000.

Reynolds, D., 2002, *Scarcity and Growth Considering Oil and Energy: An Alternative Neo-Classical View*, Edwin Mellen Press.

Shoup, C. S. (1964) "Standards for Distributing a Free Governmental Service: Crime Prevention", Public Finance, vol. 19, no. 4, pp. 383-92.

Sigman, H., "Does trade promote environmental coordination?: Pollution in International Rivers," *Contributions to Economic Policy and Analysis*, 2004, vol. 3, no. 2, article 2.

Sigman, H., "International spillovers and water quality in rivers: Do countries free ride?" *American Economic Review*, 2002, 92, 1152-1159.

Substance Abuse and Mental Health Services Administration, Dept. of Health and Human Services, *National Household Survey on Drug Abuse*: 1979, 1982, 1985, 1988, 1990-2003.

Traffic in Opium and Other Dangerous Drugs. Bureau of Narcotics, US Dept of Treasury. Washington: US Government Printing Office 1954.

Uniform crime reports for the United States. Washington : Bureau of Investigation, U.S. Dept. of Justice : U.S. G.P.O., 1930-2004.

United Nations Environment Programme. *GEO Data Portal*. Online http://geodata.grid.unep.ch/. Downloaded February, 2005.

U.S. Bureau of the Census. U.S. Bureau of the Census [producer]. U.S. Bureau of the Census [distributor]. Note: Census stock no. PE-11. Data received from Census as single-year files and were reformatted by CISER. Codebook: CPH-057.

Van Quyen, N., "Exhaustible Resources – A Theory of Exploration," *Review of Economics Studies*, 1991, 58, 777-789.

William, Jay R., J. Redlinger, and Peter K. Manning. "Police Narcotics Control: Patterns and Strategies", (Washington): Dept. of Justice, Law Enforcement Assistance Administration, National Institute of Law Enforcement and Criminal Justice, 1979.

Vita

Conan Christopher Crum was born on June 21, 1981 in Phoenix, AZ. He was the first born of five children to Robert and Kimberly Crum. He received his Bachelor of Arts in economics from The University of Arizona in May of 2003. In August of 2003, he began his graduate work in economics at The University of Texas at Austin. On March 18, 2006 Conan Christopher Crum married Amy Elizabeth Bryce.

Permanent address: 3814 E. Mountain View Rd, Phoenix, AZ 85028

This dissertation was typed by Conan Christopher Crum.